

Article

A Deep Learning Method for Facies Recognition from Core Images and Its Application: A Case Study of Mackay River Oil Sands Reservoir

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Abstract: There is a large amount of drilling core data in the Mackay River oil sands block in Canada, and the accurate identification of facies from the cores is important and necessary for the understanding of the subsurface reservoir. The traditional recognition method of facies from cores is by human work and is very time consuming. Furthermore, the results are different according to different geologists because of the subjective judgment criterion. An efficient and objective method is important to solve the above problem. In this paper, the deep learning image-recognition algorithm is used to automatically and intelligently recognize the facies type from the core image. Through a series of high-reliability preprocessing operations, such as cropping, segmentation, rotation transformation, and noise removal of the original core image, that have been manually identified, the key feature information in the images is extracted based on the ResNet50 convolutional neural network. On the dataset of about 200 core images from 13 facies, an intelligent identification system of facies from core images is constructed, which realizes automatic facies identification from core images. Comparing this method with traditional convolutional neural networks and support vector machines (SVM), the results show that the recognition accuracy of this model is as high as 91.12%, which is higher than the other two models. It is also shown that for a relatively special dataset, such as core images, it is necessary to rely on their global features in order to classify them, and, with a large similarity between some of the categories, it is extremely difficult to classify them. The selection of a suitable neural network model can have a great impact on the accuracy of recognition results. Then, the recognized facies are input as hard data to construct the three-dimensional facies model, which reveals the complex heterogeneity and distribution of the subsurface reservoir for further exploration and development.

Keywords: deep learning; core image facies recognition; Mackay River oil sands; Canada; sparse datasets; ResNet50 convolutional neural network

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1. Introduction

In the field of subsurface geology of oil and gas fields, core data obtained from drilling are the first-hand data for studying stratigraphic structure and facies type, which has high credibility and is the basis of oil and gas field exploration and development [1]. Through the facies identification and analysis from core images, we can have a certain understanding of the geological sedimentary structure of the study area and provide basic support for the reservoir prediction [2]. There are a large number of coring well photographs in the oil sands of Mackay River, Canada, which are useful information for under-

standing the subsurface reservoir. For the core image of facies identification, the traditional method is mainly by human recognition [3]; the workload of human identification of facies from core image is huge. Furthermore, the results are influenced by a lot of subjective factors, especially for ambiguous areas, of which different geologists have different interpretations and therefore pose a hard choice. In view of the above problems, a new technology is urgently needed to replace manual identification from core images, which must ensure objectivity and improve time efficiency.

With the development of artificial intelligence technology, computers are gradually replacing humans to carry out some complex and tedious tasks. In the geoscience domain, image recognition technology is introduced for core lithofacies judgement [4]. The classic one is the core recognition algorithm based on a support vector machine (SVM) proposed by Wang et al. This method extracts the color and texture features in the image and combines with SVM to train the core image, and the recognition accuracy can reach 86% [5]. However, limited by the algorithm itself, the SVM algorithm is more suitable for binary classification problems and its use is difficult for multi-classification problems. Furthermore, the SVM algorithm is difficult to implement for large-scale training samples [6]. Song et al. proposed an intelligent identification method of core slices based on a generative adversarial neural network. They first used the data of a core slice to perform adversarial training on the generated adversarial model, then used the trained generator to generate simulated images to expand the dataset, and finally transferred the convolution parameters of the discriminator to the lithology identification model to establish the lithology identification model of the core slice. The so-called core slice identification method of “WGAN+ discriminator parameter migration” solves the problem of insufficient training datasets and further improves the lithology identification accuracy. The model reaches an accuracy of 94.93% [7]. However, most of the datasets used in the training of this method come from the simulated images generated by GAN with errors smaller than the set threshold, rather than the real core images, which will undoubtedly affect the subsequent training and thus affect the recognition accuracy. Therefore, when a traditional convolutional neural network is selected for core image recognition, it is necessary to superimpose convolutional layers and increase the number of convolutional kernels in order to obtain the global features in the image, which will produce the problem of gradient disappearance or gradient explosion for the traditional convolutional neural network, meaning that the model accuracy stagnates at a certain position and cannot be further improved [8]. The shallow convolutional neural network has a poor recognition effect because it cannot learn a large number of features [9]. In the Mackay River oil sands block, a large number of core images were collected and combined with the deep learning ResNet50 model in the first attempt. Compared with the traditional convolutional neural network, the ResNet network model makes adjustments to the structure of the traditional convolutional neural network by adding directly connected channels between the convolutional layers to connect the non-adjacent convolutional layers directly, which cleverly solves the problem of gradient disappearance and gradient explosion [10]. Thus, ResNet50 network can better learn the global features of core images and is more suitable for core image recognition. In this paper, the effect of the method is tested by the actual core image recognition of Mackay River block. The results show that the recognition accuracy of the model training set of the method is better than other methods, and it can be applied in real reservoir facies recognition.

2. Overview of Study Area

Canada has very rich unconventional oil and gas resources, and its proven oil sands reserves rank first in the world [11]. Mackay River oil sands block is located in the east of the Athabasca region, Alberta, covering an area of 760 km² [12]. The Lower Cretaceous McMurray Formation reservoir is the main target reservoir for oil sands research [13]. The study area is a NW monocline structure with no fault development. The buried depth of

oil sand reservoir is about 160–180 m, the average net reservoir thickness is 18m, the average oil saturation is about 75%, the effective porosity is about 32%, the average permeability is 4–5 Darcy, and the ratio of vertical and horizontal permeability is about 0.6–1.0 [14]. There are 281 evaluation wells, 168 are core wells. There are a large number of core wells in the Mackay River oil sands block, and each well is relatively complete, with abundant core data. The core image data of the entire section are arranged in order of the original depth values, and the image data are well preserved and of high resolution. Image length and width resolution is mostly $228 \times 200,000 \pm$ dpi, the horizontal resolution and vertical resolution were 96dpi, and the bit depth was 32. The difference between different types of core images is not very obvious, mainly between colors, followed by surface texture, whether there are cracks, and whether the surface is smooth or granular (Figure 1). Facies recognition of core images by human judgement alone has low efficiency and accuracy, while deep learning image recognition can learn subtle changes and differences in images [15], and is supported by a large number of core image data, which can solve the problem of core recognition efficiently and accurately.

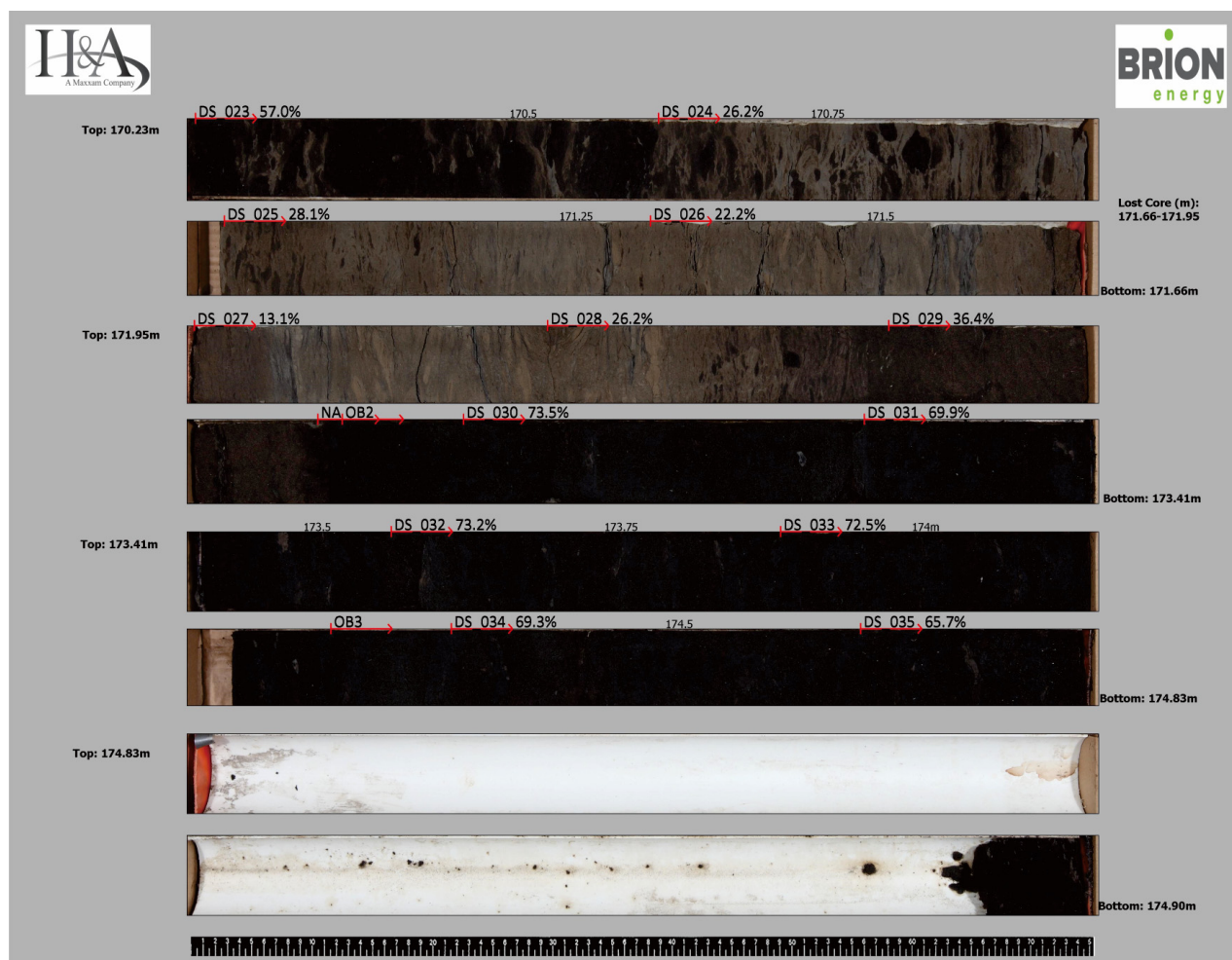


Figure 1. Typical core photograph of the study area.

3. Method

3.1. Theory of ResNet algorithm

The Residual Neural Network (ResNet) was proposed in this study. ResNet is the main idea in the network, and it increases the direct channel [16], the Highway Network (Figure 2). The emergence of the ResNet network enables deeper networks to receive better training. The principle is that the network of layer N is obtained from the network of layer N-1 through H transformation and is directly connected to the network of the previous layer on this basis, so that the gradient can receive better propagation. Therefore, it can be used to solve the problem that the training error of traditional convolutional neural networks becomes larger after increasing the number of layers. The core is to introduce the input X into the result again and map X into $F(x) + x$ through the network. The structure of ResNet can accelerate the neural network training very quickly, and the accuracy of the model is greatly improved.

$$F(x) = H(x) - x \quad (1)$$

In Equation (1), x is the observed value, $H(x)$ is the predicted value, and $F(x)$ is the actual value of residual error.

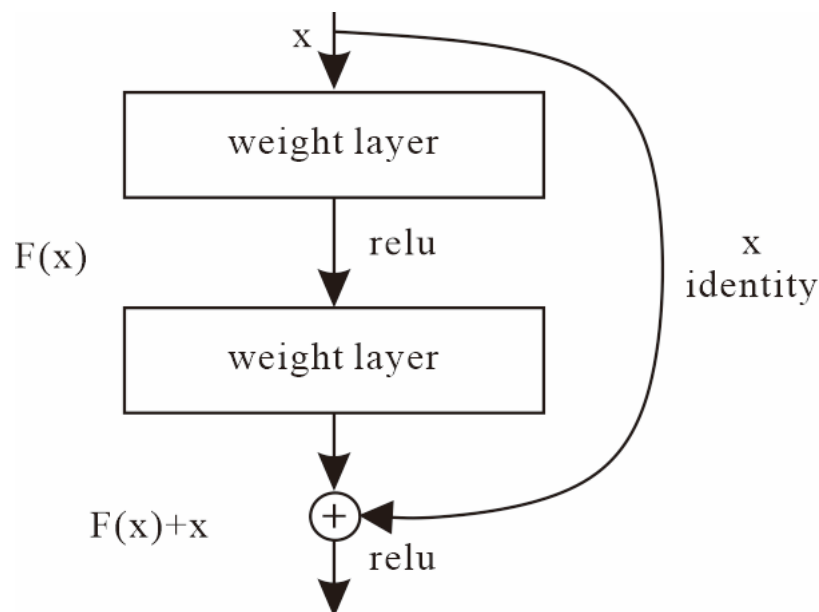


Figure 2. Residuals of ResNet50 [16].

ResNet50 is composed of three parts: input layer, hidden layer, and output layer. The input data of the input layer is the preprocessed training set, and the image size is 200×200 pixels. The hidden layer includes a pooling layer and a convolution layer. ResNet50 is divided into 5 parts, which are conv1, conv2_x, conv3_x, conv4_x, and conv5_x, respectively. In conv1, the convolution kernel is $7 \times 7 \times 64$, stride is 2, and the input is $200 \times 200 \times 3$. The output is $100 \times 100 \times 3$, and a maximum pooling layer of 3×3 with stride 2 is connected after conv1. Conv2_x, conv3_x, conv4_x, and conv5_x are all residual units, and an average pooling layer is connected after conv5_x. The convolution layer shall use the ReLU (Rectified Linear Unit) activation function to modify the linear unit, as shown in Equation (2).

$$f_{(x)} = \max(x, 0) \quad (2)$$

The functional form of Equation (2) is shown (Figure 3). ReLU activation function is a piecewise linear function, which can change all negative values to 0 while positive values remain unchanged. ReLU function has many advantages: (1) ReLU function is sparse,

which can make the sparse model mine the relevant features better and fit the training data; (2) in the region of $x > 0$, there is no gradient saturation and gradient disappearance; (3) it has low computational complexity, no exponential operation is needed, and the activation value can be obtained with only a threshold.

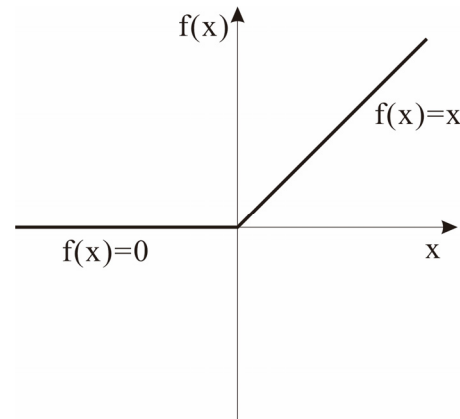


Figure 3. ReLU activation function.

The output layer is connected to the fully connected layer, and the dimension of the output is the number of categories. The softmax activation function is selected for the output layer, as shown in Equation (3).

$$\sigma(z)_j = \frac{e^{z_j}}{\sum_{k=1}^k e^{z_k}} \quad (3)$$

In Equation (3), Z_j is the output value of the j node, and k is the number of output nodes, that is, the number of classification categories. The softmax function can be used to convert the output value of multiple classifications into a probability distribution with a range of $[0,1]$ and a sum of 1. Adam is selected as the optimization algorithm of the output layer, cross-entropy loss function is selected as the loss function, and the most native accuracy is selected as the accuracy evaluation index. The loss function is shown in Equation (4).

$$c = -\frac{1}{n} \sum_{i=1}^n [y_i \ln a + (1 - y_i) \ln(1 - a)] \quad (4)$$

In Equation (4), y represents the label of sample i , positive class is 1, negative class is 0. a represents the probability that sample x is predicted to be positive class, n is the number of samples, and c represents the loss value. In core images, one of the biggest differences between different facies categories is mainly color differences (Figure 4), for example, the lithofacies F9, F10, and F12 have darker color development and are dark gray, while F2 and F6 have lighter color development and are generally light gray. The second is the surface texture of the core image, whether it is smooth or not. The surface of F2 is layered, and the surface of F5 is relatively flat with small cracks. The above features are global image features, not local features. In the field of image recognition, traditional convolutional neural networks mainly rely on local features in image recognition [17]. This is determined by the structure of the convolutional neural network, which is mainly composed of the convolutional layer, the pooling layer, and the fully connected layer. Among them, the convolution layer is mainly responsible for extracting local features in the image. The main function of the pooling layer is to reduce the amount of computation and speed up the running speed of the model on the premise of ensuring the accuracy of the results as much as possible. The main function of the full connection layer is to process

the incoming data and obtain the classification result. The convolution kernel in the convolution layer can extract the local features in the image, which are the feature points used to classify the image. However, the features extracted by the convolution kernel are all local features in the image. In order to obtain global features in the image, an often-adopted method is to superimpose convolution layers, increase the number of convolution cores, obtain more local features, and combine them into global features. Although this can achieve the purpose of obtaining global feature recognition images, for the traditional convolutional neural network, deepening the number of network layers will inevitably lead to the problem of gradient disappearance or gradient explosion, resulting in stagnation of the accuracy of the model, which cannot be further improved. In order to solve the problem of gradient disappearance and gradient explosion caused by the deepening of network layers, the ResNet network model adjusts the structure of the traditional convolutional neural network and adds a direct channel between the convolutional layers, which can directly connect the non-adjacent convolutional layers and cross the middle convolutional layer. In this way, the problem of gradient disappearance or gradient explosion can be solved. Therefore, ResNet network is more suitable for global feature classification than traditional convolutional neural networks. Therefore, it is more suitable for core image data recognition. The types of lithofacies and corresponding sedimentary microfacies in the study area are shown as follows (Figure 5).

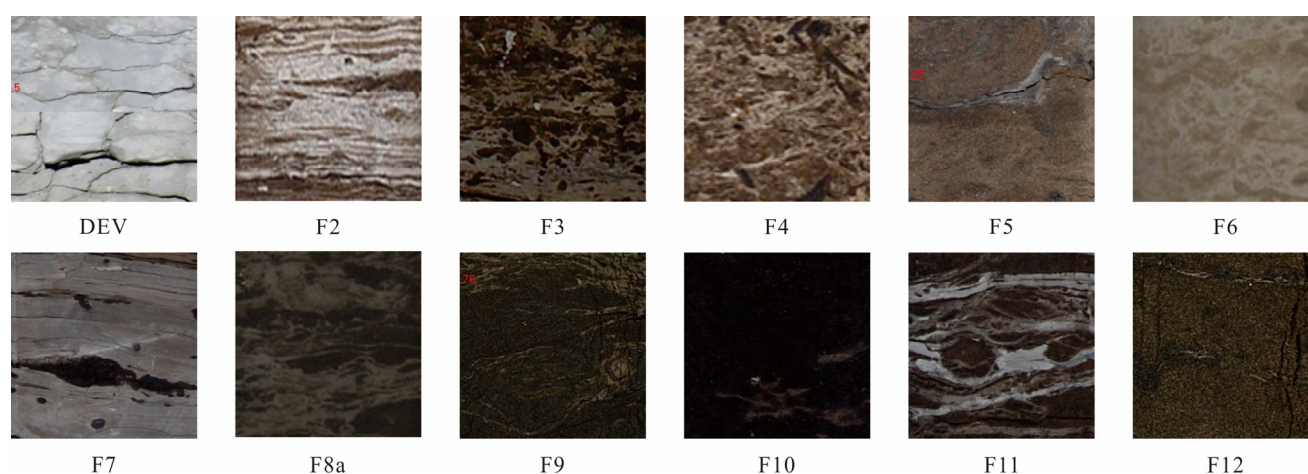


Figure 4. Categories of lithofacies.

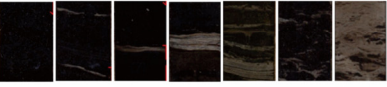
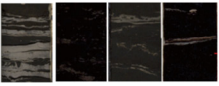
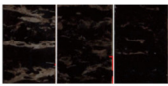
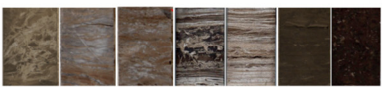
Sedimentary microfacies	Lithofacies	Lithofacies characterization	Genetic classification and characteristics
Tidal sand bar	F10, F11, F12		Tidal sand bars usually develop single-layer, double-layer and multi-layer interlayers, which have obvious bedding and form relatively fine interlayers under hydrodynamic conditions.
Sand flat	F9		Storm disturbance discontinuous interlayer, Suspended sedimentary interlayer in low-lying sandy flat, Weakly biodisturbed interlayer.
Mixed flat	F8a		Tidal beds and mudstone interbeds subjected to intense biological disturbances.
Point bar	F2, F3, F5, F6		A variety of interlayers are developed in Point bar, and the interlayers with cross bedding are common in large sections, which have strong continuity.
Salt marsh	F4, F7		The sand filled channel has high sand content and hydrostatic stable mudstone deposition.

Figure 5. Types of lithofacies and corresponding sedimentary microfacies.

In this paper, a deep learning ResNet50 neural network was combined to carry out research on lithology recognition of core images. The recognition process mainly included obtaining the original data set, preprocessing the original data set, training ResNet50 network, and using the trained model to recognize unknown core images (Figure 6).

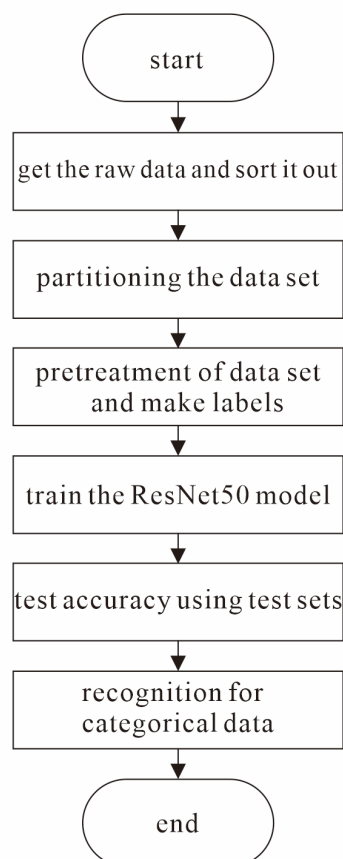


Figure 6. Flow chart.

3.2. Image preprocessing

For the initial core image data from a whole core well, the image size was large, and the resolution was $228 \times 200,000 \pm$ pixels, which is not suitable for subsequent operations. Therefore, it was necessary to cut the core well data with high reliability. First, we selected the part of the core well data to manually discriminate the facies type with high reliability, then preliminarily cut the core image according to the discriminant results, and finally cut the core image into multiple images according to the adjacent category boundary. At this time, the longitudinal size was greatly reduced, but the size of images was different, which required further clipping. The image library function in Python was used to further clipping according to the unified resolution size of 200×200 , and the core image of each category was obtained with the resolution size of 200×200 . Some images cannot reflect the original features due to the shooting angle problem, illumination problem or the core surface covered with occlusions. Such data were classified as noise data, which needed to be eliminated to ensure that they did not affect the accuracy of the model. We deleted some data after the data had a large difference between each category, which ensures the model has good robustness and has less need for data categories based on the available data set extended [18]. To solve the problem of unbalanced data volume, the data set was expanded mainly by clockwise rotation of 90° , 180° , 270° (Figure 7).

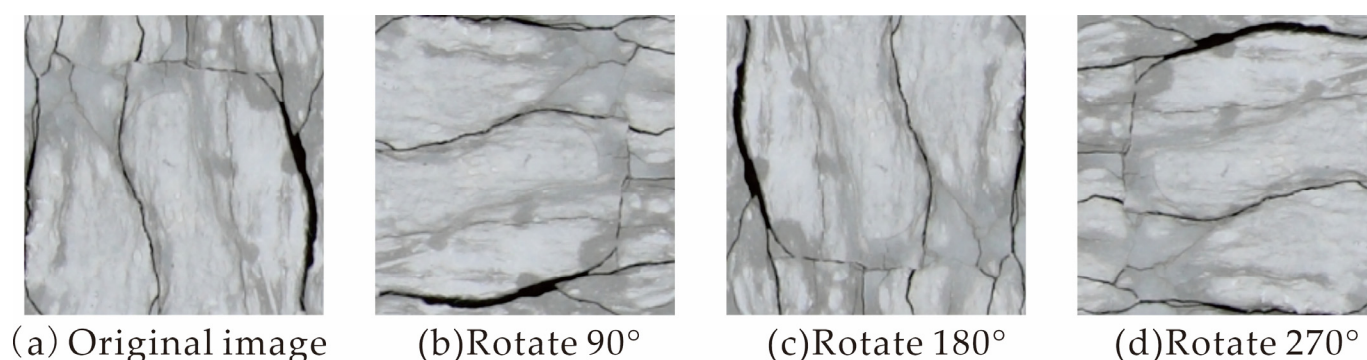


Figure 7. Rotation dataset.

3.3. Produce Label

The next step was to make labels for preprocessed images and divide the data sets. Labels of data sets according to the field of target detection in deep learning were made by manual labeling. The main idea was to read all the pictures in a folder and label them uniformly. After the labels were made, the data set could be divided into training set and test set. In this paper, since there were not too many core data in each category, too large or too small percentages of training and testing sets could have led to large differences in the number of training and testing sets, which affected the accuracy of model training results; therefore, the data sets were divided according to the ratio of 8:2. For each category, 80% of them were randomly selected as the training set and the remaining 20% as the test set. The number of training and test sets for each category is shown in Table 1:

Table 1. Quantity of training set and test set.

Lithic Facies	Number of Training Sets	Number of Test Sets
DEV	171	43
F2	156	39
F3	158	40
F4	162	41
F5	160	40
F6	166	42
F7	158	40
F8a	160	40
F9	170	43
F10	160	40
F11	174	44
F12	168	42
Background	120	30

3.4. Training Model

After the preprocessing of the core image dataset was completed, the model training could be carried out. A good model needs a set of appropriate hyperparameter combinations [19]. Usually, in order to explore the most suitable hyperparameters, the control variable method is adopted, in which the less important hyperparameters are kept unchanged and only the key one is changed. In this paper, the adjustment of hyperparameters mainly focused on the learning rate, supplemented by batch_size and epoch. The setting of the learning rate dynamically adjusts the size of the learning rate according to the training rounds, and the learning rate gradually decreases with the increase of training rounds, as shown in Equation (5).

$$\text{decayed_lr} = \text{lr}_0 * (\text{decay_rate} \wedge (\text{global_steps} / \text{decay_steps})) \quad (5)$$

In Equation (5), decayed_lr is the learning rate after attenuation, namely the real learning rate used in current training; lr₀ is the initial learning rate; decay_rate is the decay rate, namely the proportion of each decay; global_steps is the number of current training steps; decay_steps is the number of decay steps, that is, how many steps each decay is. During the experiment, epoch was set as 150, the batch size of each training was 32, decay_rate was set as 0.5, decay_steps was set as 10, and the initial learning rate was adjusted. The simulation record was shown in Table 2. We can see that the accuracy of the test set first tends to increase as the initial learning rate increases, and then tends to decrease after reaching the optimal parameters. This indicates that neither too large nor too small initial learning rate can train the best model, and also shows that ResNet50 can better simulate petrographic data when a suitable set of parameters is selected.

Table 2. Model accuracies corresponding to different initial learning rates.

Epoch	Batch_Size	lr ₀	Train Set Accuracy	Test Set Accuracy
150	32	0.01	0.9957	0.8171
150	32	0.001	0.9982	0.8407
150	32	0.0005	0.9985	0.9122
150	32	0.0001	0.9884	0.8729
150	32	0.00005	0.9963	0.8689

Preliminarily, it was obtained that the ResNet50 model can achieve better accuracy in the training and test sets with hyperparameter settings of 150 training rounds, 32 training batch size, and an initial learning rate of 0.0005. The confusion matrix of the test set under the current hyper-parameter settings was counted and the results are shown in Table 3.

Table 3. Confusion matrix at optimal hyperparameter combination.

Real Category \ Prediction Category													
	DEV	F2	F3	F4	F5	F6	F7	F8a	F9	F10	F11	F12	Background
DEV	43	0	0	0	0	0	0	0	0	0	0	0	0
F2	0	35	0	0	0	0	0	0	0	0	4	0	0
F3	0	0	35	0	0	3	0	0	2	0	0	0	0
F4	0	0	0	36	0	2	0	0	3	0	0	0	0
F5	0	0	0	0	35	0	0	0	0	0	5	0	0
F6	0	0	0	0	0	38	0	0	4	0	0	0	0
F7	0	0	0	0	0	0	37	0	0	0	3	0	0
F8a	0	0	0	0	2	0	0	38	0	0	0	0	0
F9	0	0	0	0	0	1	0	0	37	5	0	0	0
F10	0	1	0	0	0	0	0	0	6	33	0	0	0
F11	0	0	0	0	2	0	0	0	0	3	39	0	0
F12	0	0	0	0	0	0	0	0	0	0	0	42	0
Background	0	0	0	0	0	0	0	0	0	0	0	0	30

By observing the confusion matrix, it can be found that it is difficult to perform category delineation between certain petrographic categories; for example, for F9 and F10, the probability of misclassification is higher. In this way, after the initial identification of the unknown petrographic phases is completed, we can pay special attention to F9 and F10,

and manually discriminate and correct for the misclassified areas. For example, F2, F5 and F7 have been misclassified as F11. F11 also becomes a key object to be checked after the initial identification is completed, and the misclassified petrographic phases are corrected in time by manual discrimination.

3.5. Identification of Unknown Lithology

The trained model was used to test the unknown core well data. Considering that the original core data are mixed in a single image with a vertical distribution and the size is too large, the model can only identify one image as one lithology at a time, which causes the limitation that the original core image cannot be directly discriminated. To solve this problem, the sliding window recognition method [20] was adopted (Figure 8). Considering that the average pixel of the core image obtained is $228 \times 200,000 \pm$, in order to adapt to the input size of the trained recognition model, the size of the recognition window was taken as 200×200 pixels. The upper left corner of the original core image was taken as the origin of coordinates (0,0), the right direction was taken as the positive direction of the X-axis, and the downward direction was taken as the positive direction of the Y-axis to set the two-dimensional coordinate system. Starting from the origin of coordinates, the window obtains the core image data, identifies the lithology and records the results. After the contents in the current window are identified, the window will move along the positive direction of the Y-axis with a distance of 200 pixels, so as to ensure that the two adjacent windows are closely adjacent and there is no unrecognized area in the middle, which can ensure the recognition of all core images.

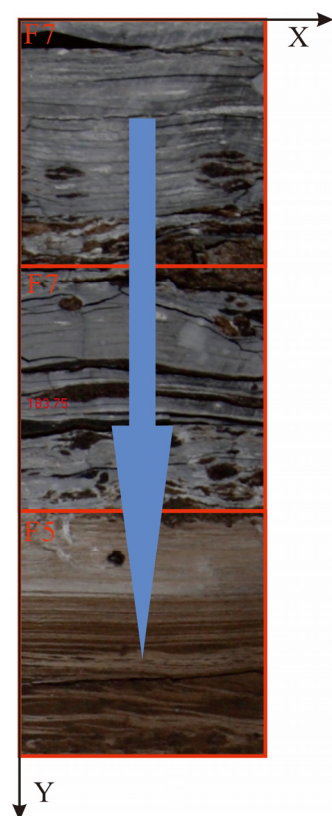


Figure 8. Moving window recognition.

The recognition results were recorded. At the same time, the starting and ending depth values were recorded, and the above steps were repeated until the entire core image was recognized. The program was written to integrate the recognition results, and the

depth values of the starting and ending positions of adjacent lithofacies of the same category were calculated to obtain the distribution depth values of each lithofacies in the core image.

4. Algorithm Comparison and Application

4.1. Algorithm Comparison

For the same training set and test set, ResNet50 neural network, traditional convolutional neural network (CNN), and SVM are simultaneously adopted to simulate the data set and adjust the hyperparameters to achieve the best performance of each model. A total of 10 coring wells in the Mackay River oil sands block were randomly selected that were not involved in the training set and test set to validate the model. The identification results were compared with the real results to calculate the accuracy. The results are shown in Table 4, and some core identification results are shown (Figure 9).

Table 4. Identification accuracy of different models.

Well Name	Accuracy (%)		
	ResNet	CNN	SVM
X1	88.23	75.92	81.33
X2	85.71	82.65	85.35
X3	83.53	80.43	81.58
X4	89.54	80.15	81.84
X5	90.56	83.88	86.66
X6	88.78	79.84	80.58
X7	91.42	86.32	84.59
X8	82.44	81.33	83.41
X9	86.88	83.75	82.45
X10	90.68	81.52	80.35

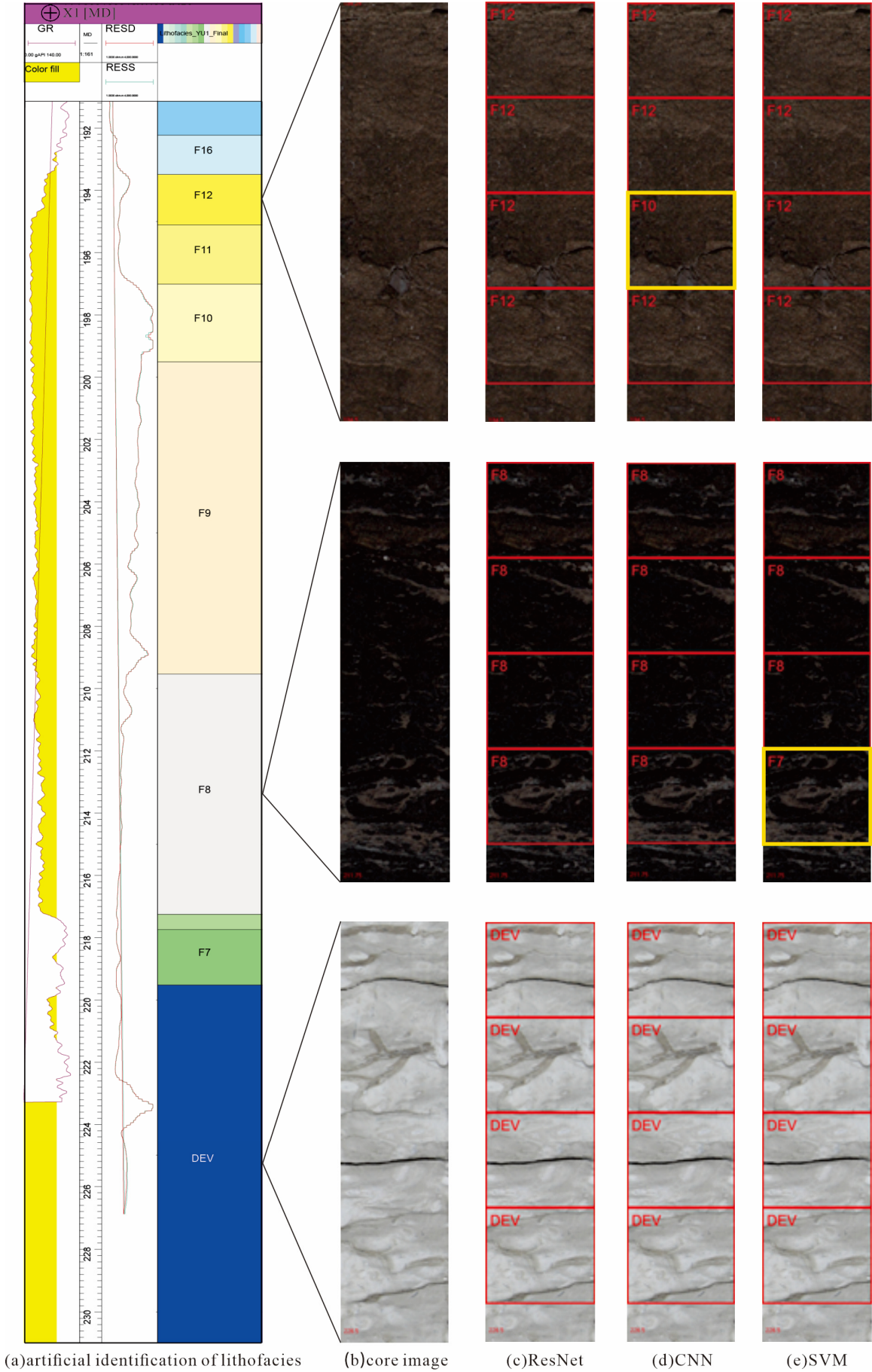


Figure 9. Core identification result.

According to the analysis of model accuracy, all the three methods can accurately identify some cores with obvious features. However, for cores with less obvious features, traditional convolutional network (CNN) and SVM will be misclassified, while the ResNet50 model can accurately identify them. The recognition accuracy of the core image shows that the ResNet50 model has the highest accuracy of 91.42%, with an average of 87.78%. Under the same test data, the CNN model has the highest recognition accuracy of 86.32%, with an average accuracy of only 81.58%, and the SVM model has the highest recognition accuracy of 86.66%. The average accuracy was 82.81%. For lithology identification of core images, the overall effect of the ResNet50 model is better than that of CNN and SVM. Therefore, the ResNet50 model was selected to identify the sedimentary facies of the remaining 168 core wells in the study area. The proportion data of different lithofacies in each well can provide lithofacies data for reservoir description quickly and accurately.

4.2. Application of Results

Through accurate core identification, combined with regional sedimentary background and seismic response, the study area was accurately determined to be tidal controlled estuarine deposition, and a typical image library of tidal controlled estuarine sedimentary facies core images was established, which provided a reference for core image recognition and sedimentary environment judgment in similar sedimentary environment [21]. Based on the determination of sedimentary facies by core images, the spatial distribution characteristics of different sedimentary facies and sand bodies can be revealed, the genesis of reservoir and the evolution law of sedimentary facies can be clarified, and the sedimentary facies model can be established through comprehensive well seismic research. Finally, using the idea of hierarchical modeling, taking the interpretation of sedimentary facies from core images as the hard condition data and seismic attributes as the constraint conditions, a fine geological model of a tided-dominated estuary in the study area was established using the method of 2D profile reconstruction of a 3D geological model [22], which laid a solid foundation for reservoir exploration and development (Figure 10).

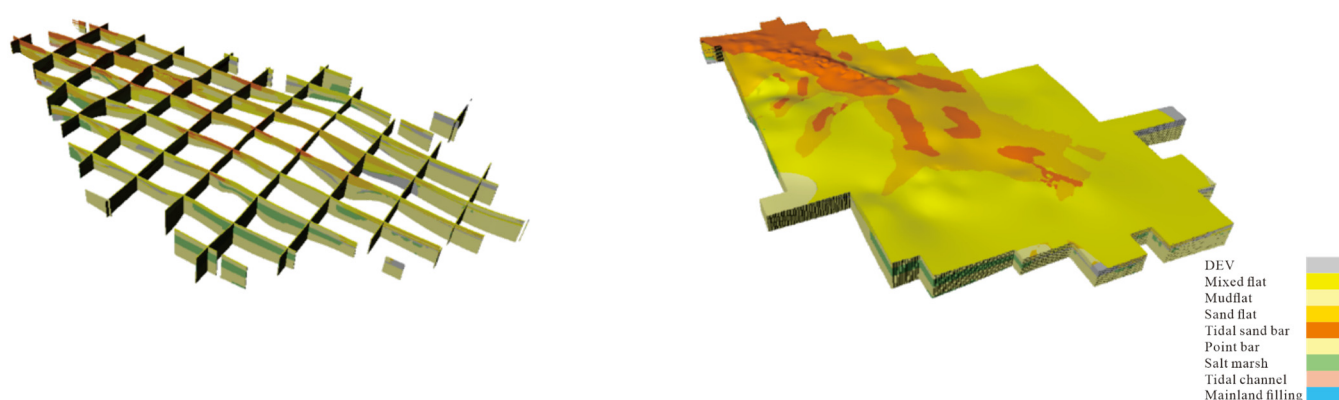


Figure 10. The 3D model of the study area.

5. Conclusions

In this paper, a new method is introduced in core image recognition, using the ResNet50 model in deep learning for lithology recognition of cores, combined with the actual block of the Mackay River in Canada, and compared with the traditional convolutional neural network model and support vector machine methods. We find that the method in

this paper greatly improves the recognition accuracy of lithology, and the analysis of test results found that the more error-prone lithology provides guidance for those identification results that require special attention manually after the initial simulation identification is completed. This method can perfectly replace the manual identification, reduce the errors caused by manual subjectivity and misinterpretation of data, and save a lot of manpower, materials, and time, while improving the accuracy of identifying lithology. It lays a solid foundation for later geological research, increases the credibility of the next work, and provides a more accurate grasp of the oil sands reservoir, which can be applied to other oil sands projects and provide a reference for the efficient development of other oil sands projects at home and abroad.

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