Applications Of Deep Learning In Unified Credit Management Of Commercial Banks

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***Abstract*—With the rapid development of new technologies, such as cloud computing, mobile internet, financial technology and big data, commercial banks in China have to step up their efforts to use new technologies such as artificial intelligence to innovate. In this paper, we focus on detecting the image orientation and rotating the image to the right angle automatically based on convolutional neural network in unified credit management of banks. First, in view of the characteristics of scanned images in banking systems, we analyze the process of credit evaluation and approval of Zhengzhou bank in detail. Then, we convert the problem of skew correction into image classification in unified credit management of commercial banks, and we fine-tuning the pretrained VGG16 model with TensorFlow for image classification. Finally, we develop a deep learning platform in bank of Zhengzhou to test the performance of the proposed method. In contrast to traditional image processing methods, the test results on bank's real dataset show the superiority of our proposed method, and the proposed method has been applied in the process of credit approval to improve the automation and intelligence level of Zhengzhou Bank to a certain extent.**

Keywords- Unified Credit Management; Deep Learning; Image Orientation; Skew Correct

I. INTRODUCTION

Deep learning has established many new state of the art solutions in the last decade in areas such as object, scene and speech recognition [1]. In particular Convolutional Neural Network (CNN) has been generalized since the breakthrough in the 2012 ImageNet Large Scale Visual Recognition Challenge of Krizhevsky [2-3], and improved the state of art of many machine vision tasks. Its architecture is indeed well suited to object analysis by learning and classifying complex (deep) features that represent parts of an object or the object itself.

As businesses begin to rely more on data-driven Artificial Intelligence applications, the new applications lead to new business issues, security, and privacy concerns. Bank can use AI Deep Learning techniques to identify erroneous or incomplete data to avoid misleading decisions. The new AI applications introduce a number of business, security and privacy issues which will have to be addressed. Neural Network, Natural Language Processing, Image Recognition, Speech Recognition and Sentimental Analysis techniques are Deep Learning techniques used in Commercial Banks and Financial Services [4].

In this paper, we study on the optimization of the process of credit evaluation and approval in commercial banks based on deep learning. Aiming at correcting 4 types of skewed images during credit approval in unified credit management system, a new skew correction method which converts the problem of skew correction into image classification is proposed. Our strategy based on convolutional neural network is to remove the final layer of the pre-trained VGG16 network [5] and add a new layer of required classes. Then retain only the new layer after freezing all other layers by using image dataset obtained in unified credit management system of commercial banks. The comparable results show that proposed method performs better than several traditional skew correction methods.

II. UNIFIED CREDIT MANAGEMENT

In order to optimize the process of credit approval in banks, it is necessary to take a close look at the process of banking credit evaluation and approval. The quality of credit approval process depends on two factors, i.e. a transparent and comprehensive presentation of the risks when granting the loan on the one hand, and an adequate assessment of these risks on the other hand. Furthermore, the level of efficiency of the credit approval process is an important rating element. Due to the considerable differences in the nature of various borrowers (e.g. private persons, listed companies, sovereigns, etc.) and the assets to be financed (e.g. residential real estate, production plants, machinery, etc.) as well the large number of products and their complexity [6].

A. Workflow of Credit Approval in Banks

The detailed process of credit approval in Chinese commercial banks involves several systems, such as Business system, Unified Credit Management system, Image platform, Core banking system and Rating system. It can be divided into six steps: Customer management, Credit management, Applying for business, Contract management, Account management and Core Banking repayment. The flowchart of unified credit management can be shown as Figure 1.

(1) Customer management. When dealing with corporate and trade finance business, cross business of small-sized enterprises and corporate credit, as well as investment banking business, account managers log into

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business system and complete the financier's information (basic information, capital structure, senior managers information, financial statements, etc.). The customers' unstructured data is uploaded to the image platform while the structured data is stored in the database of unified credit management system. Then the procedure jumps to the rating system to get rating results.

(2) Credit management. After initiating a credit application, credit approver generates the credit line based on customer's structured data from relational database and unstructured image data from image platform.

(3) Applying for business. Business contracts are generated after the business approver approves it.

(4) Contract management. When the contract is signed in the business system, the change of occupied credit limit is sent to the unified credit management system in real time.

(5) Account management. After the payment application is approved, a payment authorization is generated. The prospective borrower can apply for a loan payment from the core banking system.

(6) Core Banking repayment. If a financier pays back commercial banks' loan, the credit limit will be restored immediately in the Unified Credit Management system.

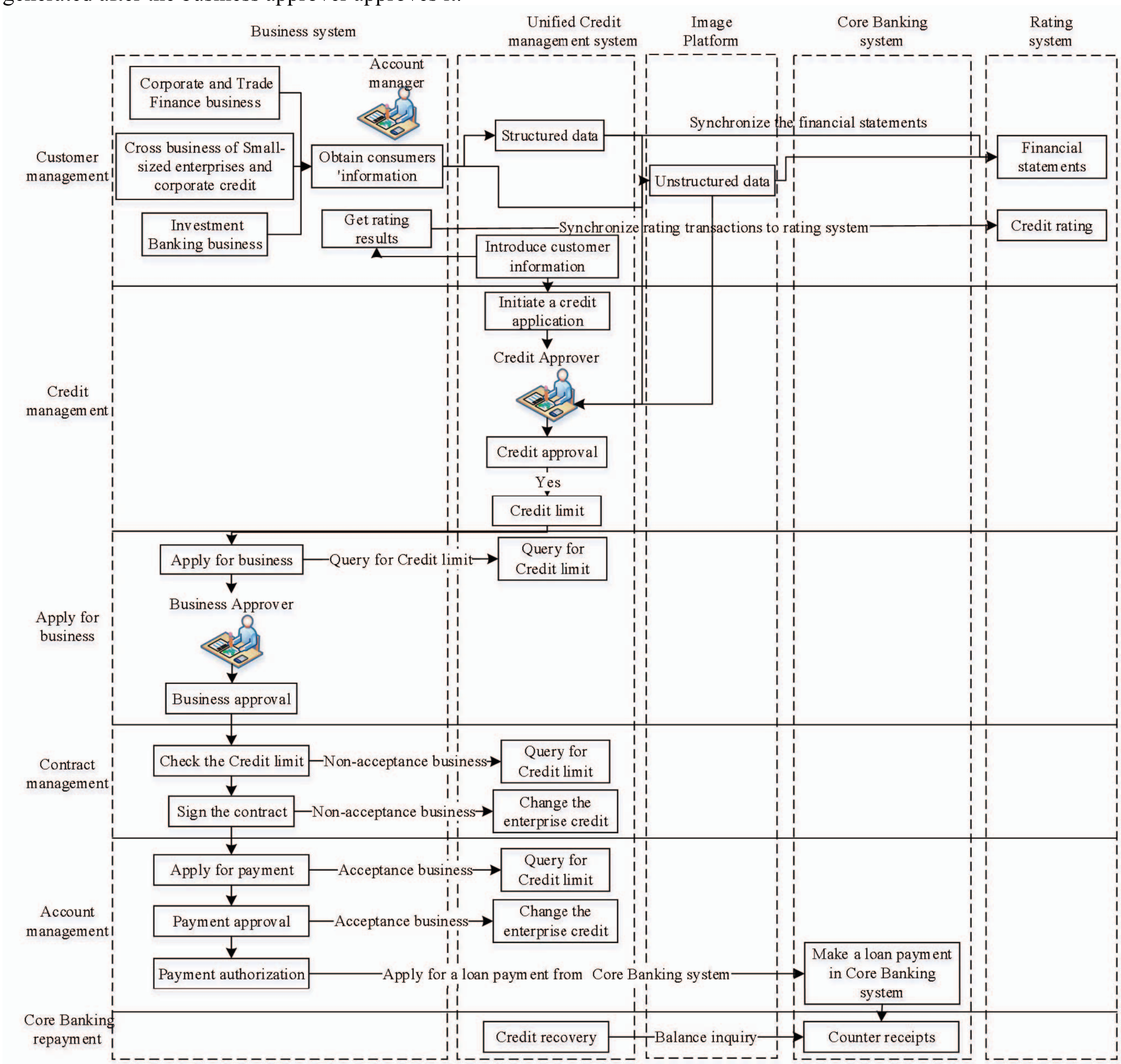

Figure 1. Flowchart of Unified Credit Management in Commercial Banks

B. Skewed Images in Credit Approval

In the process of credit approval, account manager needs to complete the financier's information, which includes structured data and unstructured image data. Structured data (such as customer number, customer name, customer type, customer manager and sub branch, etc.) is directly stored in the corresponding system database, and unstructured data (such as ID card, permit for opening bank account, business license, signature card, invoice and other image data) is uploaded to the image platform. Then the credit approver generates the credit line based on these structured data and unstructured image data. Account managers in banks often use scanners to scan paper documents and then convert them to digital images. There are only 3 types of skewness (such as 90º,180º and 270º) in scanned images. Figure 2 shows 3 types of skewed images in credit approval. When checking these skewed images, credit approvers have to rotate them to the correct angle manually.

Figure 2. Skewed images in credit approval

III. SKEW CORRECTION BASED ON VGG16 MODEL

As shown in Section 2.1. Our target is to detect the orientation of the scanned image according to text direction in it and rotate the image to the right angle automatically.

Orientation correction is a long-standing task in document analysis. However, all these methods exploit the special structure of document images, such as text layout in lines and precise shapes of letters. In the general setting, the task is harder, since important features, such as text or picture boundaries are not available and even image features, such as the horizon or other dominant horizontal or vertical lines in the scene can be missing [7,8].

In terms of correcting skewed images in the process of credit approval, fine-tuning is applied to a pre-trained VGG16 model that has been trained before on a different dataset to keep learnt weights as initial parameters. We remove the last set of fully-connected layers of this model, and replace them with our new set of fully-connected layers with random initializations along with our SoftMax classifier, freezing the rest of the network so their weight cannot be updated when the errors propagate backwards. Figure 3 shows the network structure of our method based on VGG16 architecture.

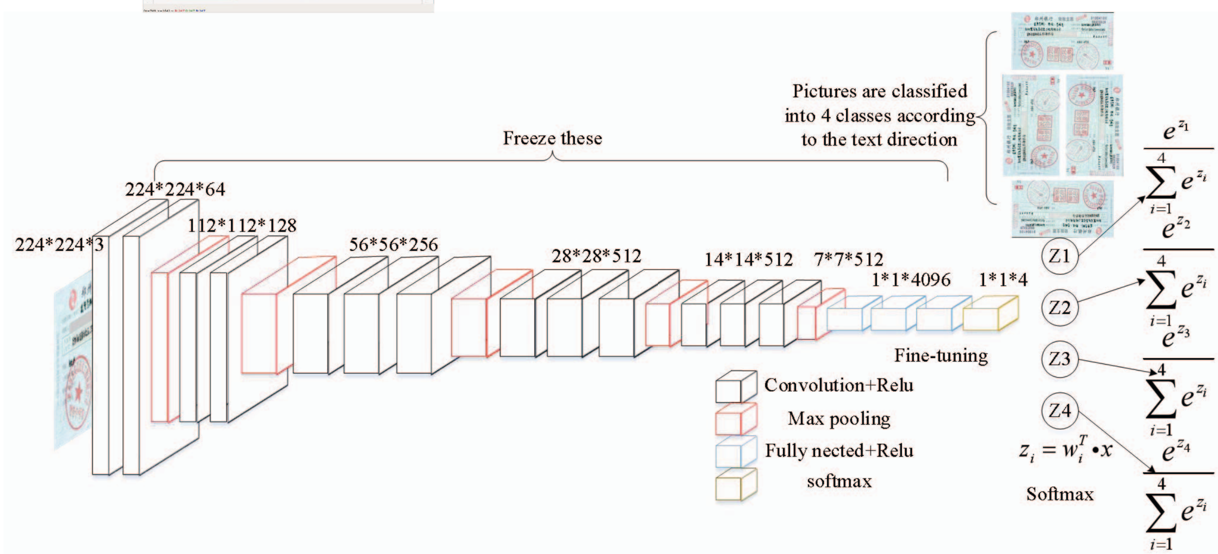

Figure 3. The network structure of our method based on VGG16

In Figure 3, three Fully-Connected (FC) layers follow a stack of convolutional layers: the first two have 4096 channels each, the third performs 4-way direction classification and thus contains 4 channels (one for each class). The network with 4-class output corresponds to 0, 90, 180 and 270 degrees:

- The bottom-to-top direction(0^o)
- The left-to-right direction(90^o)
- The top-to-bottom direction(180^o)
- The right-to-left direction(270^o)

The final layer is the SoftMax classifier. As shown in Figure 3, the output is the multiplication of the input with a weight matrix plus a bias offset, i.e.:

$$z_i = w_i^T \bullet x + b_i \quad (1)$$

For classification task, we use a SoftMax function to assign probability to each class given the input feature map:

$$p = softmax\left(Wx + b\right) \quad (2)$$

In training, we know the label given the input image, hence, we want to minimize the negative log probability of the given label:

$$L_i = -log\left(p_{y_i}\right) \quad (3)$$

where y_i is the label of the input. This is the objective function to optimize.

Skewed images in credit approval could be rotated to the right angle automatically according to the classification results of our proposed method, which can improve the process of credit approval effectively in commercial banks.

IV. Experimental Results and Analysis

A. Experimental Environment and Datasets

To check the performance of our proposed method, we develop a deep learning platform in data management center of Zhengzhou bank. Table 1 and table 2 show the hardware and software configuration of our deep learning workstation.

Table 1 Hardware configuration of our workstation

ThinkPad workstation		
Hardware	Configuration	Number
CPU	Intel(R) Xeon(R) Silver 4116 CPU @ 2.10GHz	2
Memory	128G / DDR4 2133	-
GPU	Nvidia Quadro P5000+ Quadro P4000	2
Hard Disk Drive	1T	1

Table 2 Software enviroment configuration

Software	Version
OS	CentOS 7.2
Anaconda	Anaconda 3.6.5
Python	Python 3.6
CUDA	CUDA 8.0
CUDNN	CUDNN 6.0
Tensorflow	Tensorflow-GPU 1.8
Keras	Keras 2.1.5
OpenCV	3.4.2

The dataset contains 2250 real images obtained in the process of credit approval in commercial banks. We also rotate each image by 0^o, 90^o, 180^o and 270^o, which results 3 different transformations from every original image. We split the dataset into training and testing (80/20), and split the training data into training and validation (again, 80/20 split).

B. Comparative Evaluation

We conduct experiments to compare the performance of our proposed method with the other 3 traditional image processing approaches (OpenCV minAreaRect, Hough Lines Transforms, FFT).

- OpenCV minAreaRect

The function calculates and returns the minimum-area bounding rectangle (possibly rotated) for a specified point set. It returns angle values in the range [-90, 0). After determining the skew angle, it applies an affine transformation to correct for the skew.

- Hough Lines Transforms

Hough transform is designed to detect the lines, using parametric representation of a line. It has the capability for locating fragmented lines in a binary image.

- FFT (Fast Fourier Transform)

The FFT of 2D image having spatial domain $f(x,y)$ of size M×N is given by following Fourier equation.

$$f\left(u,v\right) = \frac{1}{M}\sum_{x=0}^{M}\sum_{y=0}^{N} f\left(x,y\right)e^{-j2\pi\left(ux/M+vy/N\right)} \quad (4)$$

Figure 4~Figure 6 show the detailed process of skew correction using OpenCV minAreaRect, Hough Lines Transforms and FFT respectively on real images. Visually, the results (the last column of each example) look bad.

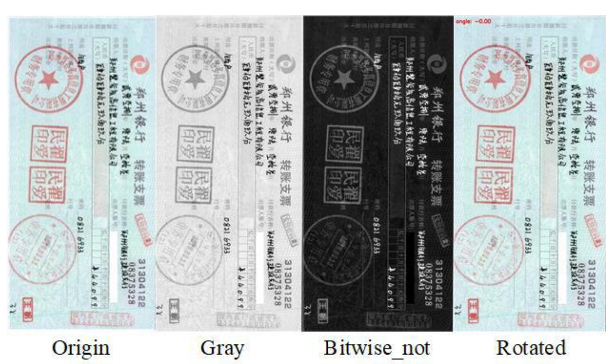

Figure 4. The process of skew correction with OpenCV minAreaRect

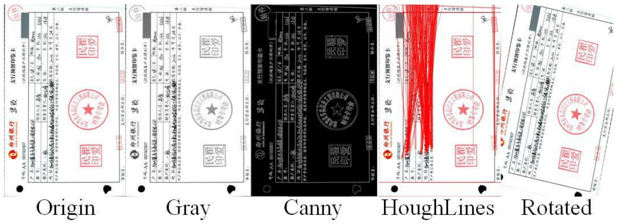

Figure 5. The process of skew correction with hough lines transforms

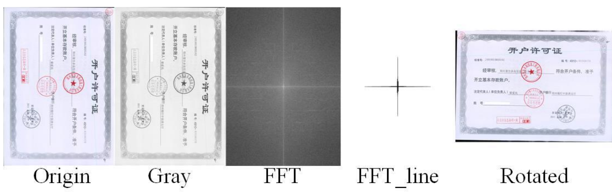

Figure 6. The process of skew correction with FFT

In order to verify the performance of our proposed method, we test it on various document images. They may only contain text, or may contain text with tables, graphics, or photographs.

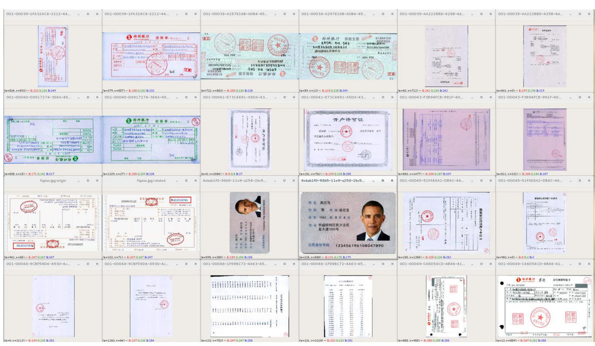

Figure 7. Results with our proposed method on real dataset

Figure 7 shows some examples for the orientation adjustment. (Odd column: Original images, Even column: Rotated images). To further validate our method, we test it on some poor-quality images acquired from image platform in Bank of Zhengzhou. Figure 8 shows that the proposed algorithm can detect the image orientation and rotate it to the right angle correctly, and it achieves 95.396% accuracy in real image dataset.

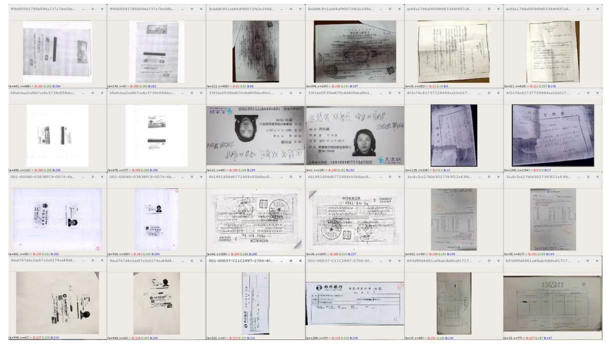

Figure 8. Results with our proposed method on some poor-quality images

V. CONCLUSIONS

In this paper, we presented an approach based on deep convolutional neural network that could detect the orientation of scanned images generated in the process of credit approval of commercial banks. This orientation predict can be used to adjust the image to its canonical orientation. The use of deep learning technology is advantageous for this task, since large numbers of training samples can be generated synthetically and the network is able to learn subtle contextual features that allow it to estimate the correct orientation automatically even when straightforward features. We have made our implementation as a part of unified credit management system in bank of Zhengzhou.

In future work the network architecture will be optimized to run in real-time on smaller graphic chips. And we will consider orientation estimation at more levels: 30º, 45º, 120º, 135º, etc.

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