Banknote Fitness Judgment System Using MemSeg Based on K-Means Memory Update

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Abstract*— In general, it is difficult to determine the authenticity of damaged banknotes, so the Bank of Korea exchanges banknotes that are not suitable for circulation due to damage or wear. In this study, we propose a banknote authenticity judgment system using MemSeg based on K-means memory update to identify damage to banknotes more objectively and quickly. When memory update is performed using K-means, normal images with various feature patterns are updated uniformly in the memory, and the experimental results show that the image-AUROC is improved by an average of 4.27% compared to the existing method, proving that the proposed method is more objective.

***Keywords*— MemSeg, Banknote, Fitness, K-means, Uniformly, Objectively**

I. INTRODUCTION

In modern society, damaged banknotes are often encountered when making cash transactions. In general, it is difficult to determine the authenticity of damaged banknotes, which can lead to counterfeiting crimes. In order to prevent such crimes, the Bank of Korea exchanges banknotes that are not suitable for circulation due to damage, contamination, or wear for banknotes suitable for circulation without fees. [1] In this process, it is important to set the allowable range of damage, contamination, and wear to distinguish between banknotes that can be circulated and those that cannot be circulated. Accurately assessing and classifying the condition of banknotes currently requires a lot of human resources, and there is a possibility that the judgment of whether or not a banknote is damaged can be subjective. Recently, deep learning technology has been developed, suggesting the possibility of automation in various image processing and classification tasks, and if financial institutions such as banks utilize this, labor will be reduced and efficient currency management will be possible. Based on this need, this study proposes a banknote authenticity judgment system using K-means memory update-based MemSeg (memory-based segmentation network) [2] [3] to objectively and efficiently detect damaged parts of banknotes.

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II. RELATED WORKS

Previous approaches[4] classified the status of three banknotes, Korean Won (KRW), Indian Rupee (INR), and US Dollar (USD), into three or two grades: suitable, normal, and unsuitable based on CNN. This method has the advantage of automatically extracting features within an image using a CNN model, but has the limitation that it requires a large amount of time and a large amount of learning data to learn them. To compensate for this, MemSeg uses semi-supervised learning, which enables learning with only normal image samples. In addition, since abnormal samples are artificially generated in MemSeg and used for learning, it can produce effective results with relatively little data.

MemSeg is a semi-supervised method that uses memory modules to allow the network to remember general normal patterns and compare them with input images to identify abnormal areas. In other words, the network detects abnormal areas by comparing similarities and differences with the remembered normal images. In the training phase, MemSeg randomly selects and stores normal samples in the memory pool to learn general patterns of normal images. Then, in the inference phase, it compares the input image with the normal samples stored in the memory pool, analyzes the differences, and finds the location of the abnormality based on the differences. This method is inspired by the way humans remember, allowing the network to clearly distinguish between normal and abnormal patterns.

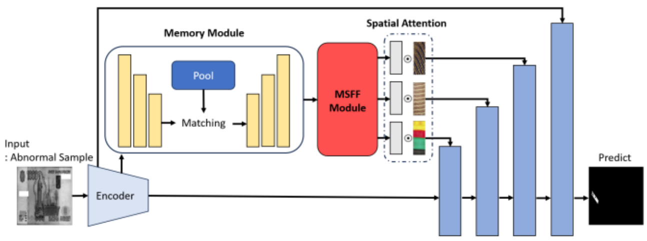

Figure 1 MemSeg Overview

As shown in Figure 1, MemSeg performs the task of detecting defects in images using a U-Net-based[5] network structure. The Encoder section uses ResNet-18[6] to extract high-dimensional features from the input image. Initially, high-dimensional features of only normal image samples are extracted and stored in the memory pool to fix the normal pattern, and based on this, the abnormal area is predicted through the Decoder section by comparing it with the input image. At this time, the L2 distance between the input image and the memory sample is calculated to extract the difference. After detecting the abnormal area, the multi-scale feature fusion module[7] and the spatial attention module are used to predict the defective area more precisely. As shown in Figure 2, a Binary Mask is created from Random Perlin Noise[8], and abnormal samples such as structural and texture abnormalities from DTD datasets[9] are artificially generated. The network is trained by predicting the Binary Mask using the generated abnormal image samples as input, and various defect patterns are learned by synthesizing multiple patterns within the Mask. It improve the performance of the model.

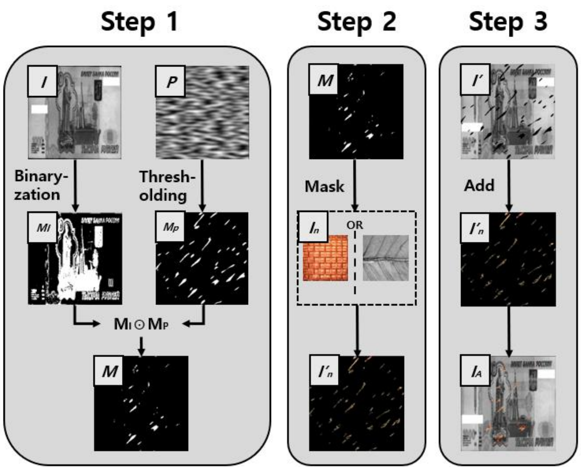

Figure 2 Abnormal sample generation process

For images acquired from banknote recognition equipment, there may be various deformations within the normal banknote range that occur while using the banknote, including Geometric Transformation that occurs during the acquisition process. Since MemSeg predicts abnormal areas from the differences between normal and abnormal patterns, it is very important to secure the diversity of normal images when initializing the memory pool consisting of high-dimensional features of normal image samples. The original random sampling method may decrease performance by repeatedly selecting normal image samples with similar high-dimensional features, and there is a possibility that performance changes significantly depending on which image sample is selected. Therefore, this study improved the accuracy of banknote authenticity judgment by updating the memory using K-means to secure the diversity of normal image feature patterns and the stability of selecting normal image samples.

III. METHOD

This study was conducted using approximately 20,570 visible light reflectance images provided by Company A. The datasets consists of eight types of Russian banknotes: 50_RUB, 100_RUB (old), 100_RUB (new), 200_RUB, 500_RUB, 1000_RUB, 2000_RUB, and 5000_RUB. Each banknote type consists of four types of images as shown in Figure 3: the front and back images, and the front and back images are tilted 180 degrees.

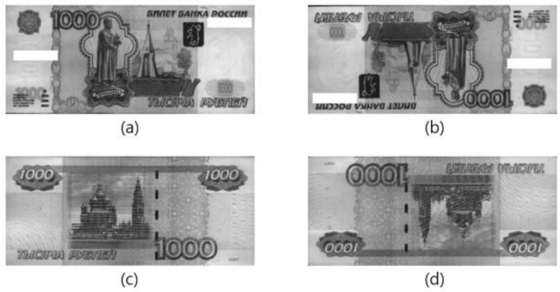

Figure 3 Example of 1000_RUB (a): front page, (b): front page rotated 180 degrees, (c): back page, (d): back page rotated 180 degrees

Abnormal datasets were classified as a test set, and these were classified into 10 defects, Stain, Graffiti, De-inked, 8%_Soiled, Tape, Tear_dogear_etc., as shown in Table 1 below, referring to “The Bank of Russia Notes Fitness Criteria” of the Central Bank of Russia [10]. Through this, the prediction for each defect was visually confirmed.

Table 1 List of criteria for each defect of the Central Bank of Russia

Defect	Definition	Minimum standard
Stain	Staining or contamination of some areas	If one area is 20mm^2 or more
Graffiti	Drawings or text (using pens, stamps, etc.)	If there are more than one symbol, character, or unauthorized image
De-inked	Ink fading of some or all areas	If the lack of ink can be visually confirmed
8%_Soiled	Bills with stains on the surface that reduce brightness by more than 8%	If the stain is confirmed using a spectrophotometer or colorimetric device
Tape	Contamination from tape	If the defect is caused by tape and cannot be visually recognized
Tear_dogear_etc	One or more tears on the edges	If one or more lengths are 7mm or more

A. *Preprocessing*

In order to retrieve only the area of the banknote image from the given datasets, the ROI (Region of Interest) detection process [11] was performed. The ROI detection process is as follows. (1) The banknote image area is separated using a threshold value, and (2) the edges of the banknote image are identified using an edge detection filter and Hough transform. (3) The axis alignment process is performed using the tilted angle of the banknote image to align the tilted input banknote to the axis. In addition, Russian banknotes have unique serial numbers on both sides of the banknote to prevent counterfeiting. At this time, since the serial number affects the MemSeg experiment that compares similarity and difference, the serial number of the banknote should be covered and the study should be conducted. Therefore, as shown in Figure 3 (a) and (b), the unique serial number existing at a certain location for each banknote type was masked and preprocessed.

B. *Experiment*

Based on MemSeg described in related works, the experiment was conducted by specifying the target as 8 types of dollars. In this case, in the existing MemSeg experiment, when updating the memory sample, a randomly selected normal image is stored in the memory pool and the normal pattern is learned through this. However, in the case of randomness, there is a possibility that the 4 cases in Figure 3 are not evenly included. Therefore, in this study, a method of updating the memory using K-means[12] is proposed.

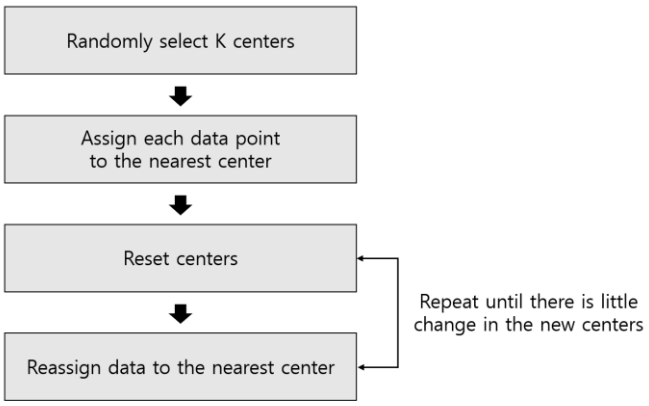

Figure 4 K-means Algorithm Flowchart

K-means is one of the representative unsupervised learning algorithms that performs data clustering. As shown in Figure 4, this algorithm (1) randomly selects K centers, (2) assigns each data point to the closest center, and uses the Euclidean distance at this time. Then, (3) resets the center of the cluster, and (4) repeats the process of reassigning data to the cluster until the center does not change. If normal images are updated in the memory pool using this K-means, images in four cases are stored uniformly as shown in Table 2 below.

Table 2 Comparison of memory pool updates by method

Direction/Method	Random	K-means
Front	9	12
Back	7	12
Front 180-degree rotation	20	12
Back 180-degree rotation	12	12
Total	48	48

IV. RESULT

Table 3 Experimental results table (image-AUROC mean and standard deviation)

Target	Average of image-AUROC (%)		Standard deviation (%)	
	random	***k-means***	***random***	***k-means***
50_RUB	80.80	88.64	14.09	2.53
100_RUB (Old)	89.90	91.02	4.07	2.13
100_RUB (New)	71.62	77.90	5.04	2.16
200_RUB	84.28	89.08	8.75	4.13
500_RUB	82.68	91.06	16.18	4.83
1000_RUB	85.02	86.26	1.86	2.26
2000_RUB	74.22	75.00	12.63	4.25
5000_RUB	77.72	81.46	8.08	3.81
Average	80.78	85.05	8.84	3.26

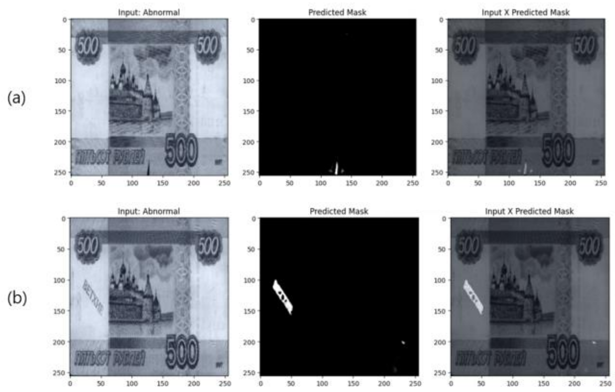

Figure 5 Model prediction examples
(a): Tear_dogear_etc example, (b): Graffiti example

Table 3 above shows the performance results of image-AUROC of the experiment in which memory was updated randomly for each type of bills and image-AUROC of the experiment in which memory was updated using K-means which is the average value when each was repeated 5 times. When looking at the results, it was confirmed that the experiment in which memory was updated using K-means improved image-AUROC by at least about 0.8% to 8% and on average 4.27% for each target compared to the previous experiment in which memory was updated randomly. In addition, when looking at the standard deviation of the experiment repeated 5 times, the K-means method showed a value that was about 5.58% lower than the random method for the entire target on average, confirming that the model was trained more stably. When I ran the demo to visually confirm, I was able to confirm the results as in Figure 5. However, among the defects mentioned above, Stain, Graffiti, Tear_dogear_etc. predicted abnormal parts well, but De-inked, 8%_Soiled, and Tape did not predict well.

V. CONCLUSTION

The MemSeg method is a semi-supervised method that detects image surface defects by comparing the commonalities and differences of images. In this study, by changing the method of updating the memory samples for comparison in the memory pool from random to K-means, it was possible to compare images in various cases evenly, and the average accuracy was also improved about 4.27%. Through this, it is judged that the MemSeg method based on K-means memory update can perform banknote authenticity judgment more objectively than the existing random MemSeg method.

However, the reason why the accuracy came out as above is thought to be due to the influence of the number of memory samples. The reason is that the number of images that can be compared increases as the number of memory samples increases, so the accuracy aspect can be improved, but it is expected to take a lot of time. In addition, the reason why De-inked, 8%_Soiled, and Tape were not predicted well is thought to be because these three defects are contaminations related to brightness changes, and the following experimental results were produced because textures or structures related to brightness were not included in the process of generating and predicting abnormal samples.

In the future work, if we determine an appropriate number of samples and conduct experiments by generating and predicting more diverse types of abnormal samples, we can expect better results when comparing the existing random MemSeg method with the K-means MemSeg method.

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