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

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Abstract*— In general, determining the authenticity of damaged banknotes can often be challenging. To address this, 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. This system identifies 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. The experimental results show that the image-AUROC is improved by an average of 4.27% compared to the existing method. This proves that the proposed method is more objective.

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

I. Introduction

In modern society, damaged banknotes are commonly encountered during cash transactions. Determining the authenticity of these damaged banknotes is challenging, potentially enabling counterfeiting crimes. To address this issue, the Bank of Korea exchanges banknotes that are damaged, contaminated, or worn out, replacing them with suitable ones at no cost[1]. In this process, setting clear standards for allowable damage, contamination, and wear is critical to distinguishing banknotes that are fit for circulation from those that are not. However, assessing the condition of banknotes requires significant human resources, and subjective judgment can lead to inconsistencies.

Recent advances in deep learning suggest the possibility of automating such tasks. With these technologies, financial institutions could reduce labor requirements while enhancing the efficiency of currency management. Motivated by this need, this study proposes a banknote authenticity judgment system. The system uses MemSeg, a memory-based segmentation network, enhanced with K-means memory updates to efficiently and objectively detect damaged areas on banknotes[2][3].

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II. Related Works

Previous approaches[4] classified the fitness of three banknotes—Korean Won (KRW), Indian Rupee (INR), and US Dollar (USD)—into three or two grades: suitable, normal, and unsuitable. These methods relied on CNNs, which automatically extract features from images. However, CNN-based models require large amounts of training data and significant processing time, limiting their practicality.

To overcome these limitations, MemSeg was introduced. MemSeg employs a semi-supervised learning framework that trains exclusively on normal image samples. It compensates for the lack of abnormal samples by artificially generating them during training, enabling effective results even with relatively small datasets. MemSeg leverages memory modules to store general patterns of normal images. The network detects anomalies by comparing input images with these stored patterns. During the training phase, as shown in Figure 1, MemSeg randomly selects and stores normal samples in a memory pool, capturing the high-dimensional features of normal images. During the inference phase, the network compares an input image with the stored patterns in the memory, calculates the differences using L2 distance, and identifies abnormal areas based on the detected differences. Inspired by human memory, this approach allows the model to clearly distinguish between normal and abnormal patterns.

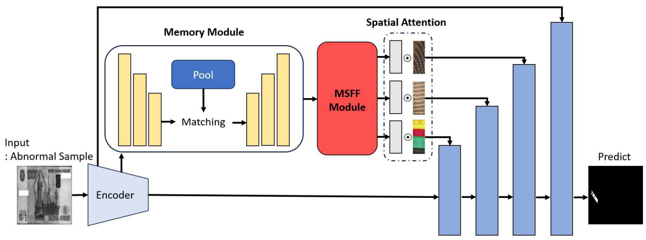

Figure 1 MemSeg Overview : The MemSeg framework employs a U-Net-based architecture with a ResNet-18 encoder to detect defects by comparing input features to normal patterns stored in a memory pool. Abnormal areas are identified and refined through multi-scale feature fusion and spatial attention.

Figure 1 illustrates how MemSeg performs defect detection using a U-Net-based network architecture[5]. In the encoder section, ResNet-18[6] extracts high-dimensional features from input images, which are stored in the memory pool. The decoder section then compares these stored features with those of the input image, predicting abnormal areas with enhanced precision. To refine these predictions further, the network incorporates multi-scale feature fusion[7] and a spatial attention module.

Artificially generating abnormal samples is critical for training MemSeg effectively. Figure 2 demonstrates this process, where a Binary Mask derived from Random Perlin Noise[8] is used to synthesize structural and texture abnormalities. These samples, combined with patterns from datasets like DTD[9], allow the network to learn and detect diverse defect patterns. By incorporating multiple patterns within the mask, the model′s performance is significantly enhanced.

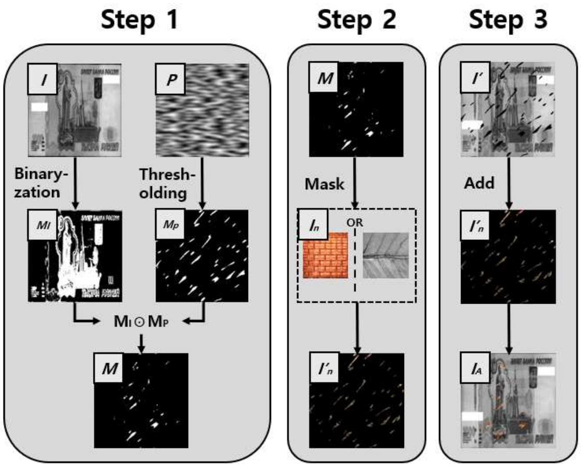

Figure 2 Abnormal sample generation process : A Binary Mask from Random Perlin Noise and DTD data generates diverse defects to train the network effectively. These make network to learn diverse defect patterns and improve performance.

Normal banknotes often exhibit variations, such as geometric transformations, during image acquisition. These variations necessitate a diverse representation of normal patterns in the memory pool. However, random sampling methods frequently result in redundant or similar samples, which reduces both accuracy and stability. To improve performance, this study adopts a K-means memory update strategy. By clustering normal image patterns, K-means ensures a more diverse representation of normal samples in the memory pool, as shown in Figure 2. This approach enhances both the accuracy and stability of the banknote authenticity judgment system, ensuring consistent results during training and inference.

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.

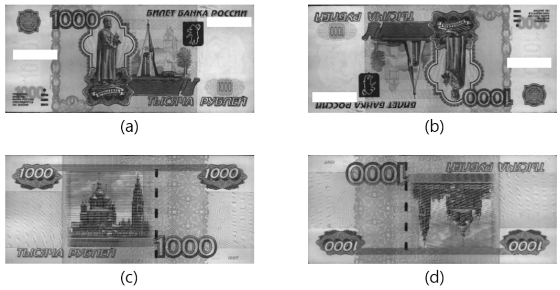

Figure 3 Example of 1000_RUB (a): front page, (b): front page rotated 180 degrees, (c): back page, (d): back page rotated 180 degrees

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

To extract the area of interest from the given datasets, a Region of Interest (ROI) detection process[11]was applied. The steps for ROI detection are as follows: (1) Separate the banknote area using a threshold value. (2) Identify the edges of the banknote image using an edge detection filter and the Hough transform. (3) Perform axis alignment by correcting the tilted angle of the input image.

In addition, Russian banknotes include unique serial numbers on both sides to prevent counterfeiting. These serial numbers can affect the MemSeg experiment by introducing unwanted differences during similarity comparisons. To mitigate this, the serial numbers were masked during preprocessing. As shown in Figure 3 (a) and (b), the serial numbers were covered before conducting the study.

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.

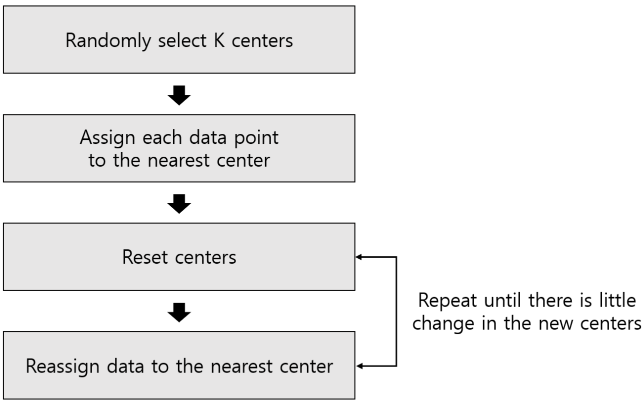

Figure 4 K-means Algorithm Flowchart

K-means, a widely used unsupervised clustering algorithm, operates as follows : (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 two methods (Random and K-means)

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. RESULTS

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

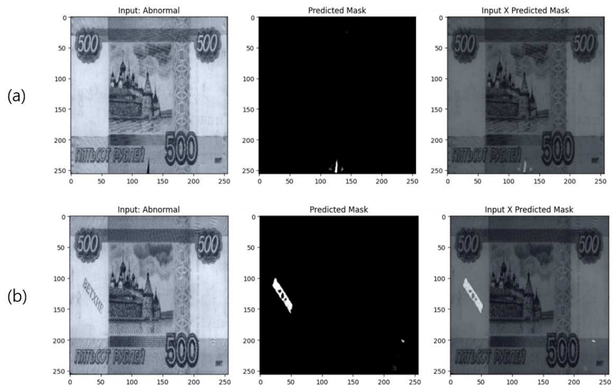

Figure 5 Model prediction examples (about 500_RUB)
(a): Tear_dogear_etc example, (b): Graffiti example

The results, summarized in Table 3, show the image-AUROC performance for each banknote type when using random sampling and the K-means memory update. AUROC (Area Under the Receiver Operating Characteristic Curve) is an indicator for evaluating the performance of a binary classification model. It calculates the area under the ROC curve to indicate the model's discriminatory ability. The closer the AUROC value is to 1, the better the model's performance, and 0.5 means the same performance as random guessing. Each experiment was repeated five times, and the average values were compared. The K-means memory update improved image-AUROC by at least 0.8% and up to 8%, with an average improvement of 4.27% across all targets. Additionally, the standard deviation of results across five repetitions was 5.58% lower for K-means compared to random sampling, indicating more stable model performance.

When tested visually, as shown in Figure 5, the model effectively predicted defects such as Stain, Graffiti, and Tear_dogear_etc.. However, defects like De-inked, 8%_Soiled, and Tape were not predicted as accurately. These defects are related to brightness changes, and the results suggest that brightness-related textures or structures were not sufficiently included during the generation of abnormal samples.

V. Conclusion

The MemSeg method is an approach to detecting image surface defects based on semi-supervised learning, and identifies defect areas by comparing similarities and differences between images. In this study, we propose a method to update memory samples by replacing the existing random sampling with K-means clustering. This makes the distribution of normal patterns more uniform and improves the average accuracy by 4.27%. This shows that the K-means-based memory update can evaluate the authenticity of banknotes more objectively than the random MemSeg method.

However, the number of memory samples has a significant effect on the accuracy improvement. As the number of memory samples increases, the number of comparison opportunities with the input image increases, which increases the accuracy, but this causes the problem of increased computation time. In addition, the reason for the low performance in certain defect types such as De-inked, 8%_Soiled, and Tape is analyzed to be due to the lack of brightness-related patterns in the generated abnormal samples.

In future studies, we will be able to improve the performance by determining the optimal number of memory samples and generating more diverse types of abnormal samples. In addition, it is expected that additional insights can be obtained by comparing the existing random MemSeg method with the K-means-based MemSeg method under these same conditions. Such improvements can enhance the model's defect detection ability. In particular, it is likely to be more effectively applied to practical banknote authenticity determination problems.

References

[1] Bank of Korea, "Currency exchange standards and methods," Bank of Korea. [Online]. Available: https://www.bok.or.kr/portal/main/contents.do?menuNo=200393. [Accessed: Oct. 13, 2024].

[2] M. Yang, P. Wu, M. Liu, and H. Feng, "MemSeg: A semi-supervised method for image surface defect detection using differences and commonalities," CoRR, vol. abs/2205.00908, 15p, 2022.

[3] TooTouch, "MemSeg: A memory-based segmentation network," GitHub repository. [Online]. Available: https://github.com/TooTouch/MemSeg. [Accessed: Oct. 13, 2024].

[4] T. D. Pham, D. T. Nguyen, C. Park and K. R. Park, “Deep Learning-Based Multinational Banknote Type and Fitness Classification with the Combined Images by Visible-Light Reflection and Infrared-Light Transmission Image Sensors,” Sensors, Vol.19(4), 2019.

[5] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," in *International Conference on Medical Image Computing and Computer-Assisted Intervention*, Munich, Germany, 2015, pp. 234-241.

[6] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Las Vegas, NV, USA, 2016, pp. 770-778.

[7] T. Y. Lin, P. Dollár, R. Girshick, K. He, B. Hariharan, and S. Belongie, “Feature pyramid networks for object detection,” In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 2117-2125, 2017.

[8] K. Perlin, "An image synthesizer," *ACM Siggraph Computer Graphics*, vol. 19, no. 3, pp. 287–296, 1985.

[9] M. Cimpoi, S. Maji, I. Kokkinos, S. Mohamed, and A. Vedaldi, "Describing textures in the wild," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Columbus, OH, USA, 2014, pp. 3606–3613.

[10] The Central Bank of the Russian Federation, " The Bank of Russia Notes Fitness Criteria," [Online]. Available: https://www.cbr.ru/eng/. [Accessed: Oct. 13, 2024].

[11] SeoHyun Kwak, "Fitness Check Method of Banknotes Using CIS Note Image," Master's thesis, Seoul National University, Seoul, South Korea, 51 pages, 2012.

[12] N. Dhanachandra, K. Manglem, and Y. J. Chanu, "Image segmentation using K-means clustering algorithm and subtractive clustering algorithm," *Procedia Computer Science*, vol. 54, pp. 764-771, 2015.