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A NOVEL MODEL OF TEXTURE PATTERN BASED OBJECT IDENTIFICATION USING CONVOLUTED MULTI-ANGULAR (CMA) PATTERN EXTRACTION METHOD

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Abstract

Computer aided machine for automation process was increasing the usage in our traditional life. There are lot of automation systems that are integrated even in the daily using equipment like smart phone that capture the image to recognize the face or any type of objects present in it. In that, most of them were focused to provide a better feature analysis method to enhance the accuracy of predicting objects in the image. To achieve this, image texture pattern helps to extract the features of image which is robust in outer intensity difference in the image. This research work proposed a novel method of texture pattern extraction was implemented in the application of object identification. The novelty of the proposed pattern extraction model refers the neighborhood pixels in the frame of window in multiple projections of angle. The estimation of magnitude from the convoluted patch of image forms the image pattern. This type of image pattern recognition process was named as Advance Convoluted Multi-Angular (ADCMA) model-based feature analysis Method. This texture-based features analysis model is classified by with the enhanced model of deep learning classification method with modified layer of pattern-based training model. The proposed method can be validated by comparing the recognition result with further competitive methods by evaluating the statistical parameters.

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1. Introduction

In the image processing applications such as face recognition, finger print recognition, object identification, medical image analysis, etc. were commonly refers the concept of image segmentation and image classifications. In the recent days, the Artificial Intelligence (AI) improves the rate of prediction and data analytics to make a decision based on the previous data pattern and its combination of results. This form of data prediction is depending on how we train the system and what are the features that we represent the data to forecast the activity. In most of the techniques that are related to automation process, it refers the clustering and classification model to recognize and predict the region of interest (ROI). This can also segment and represent as a different color to mark the position of required object in the current frame. The applications such as video tracking and other types of object identification searching for better solution to enhance the classification performance than by fixing the static rules to identify it.

To overcome the problems and to improve the performance of classification in object identification system, a novel model of image pattern extraction method was proposed in this paper. This can be achieved by the advance Convoluted Multi-Angular (ADCMA) texture pattern extraction method. In this ADCMA, the image was segmented into different cells with the standard mask size and each cell can be convoluted with the filtering coefficients. Then from that convoluted cell, the difference in magnitude between the boundary and its center of the cell can be evaluated in multiple-angles of projections to abstract the texture of an image. Finally, the binary sequence from one cell was converted into values to form it as a image pattern. The novelty of proposed work is based on the evaluation of image neighborhood pixels in different angle of the cell to represent clear structure of the object. The proposed pattern extraction method refers the enhanced model of Local Tetra Pattern (LTrP) method that is to analyses the image in multiple projection of angles.

1.1 The main intension of this paper work can be listed as

1. To improve the object identification model by using the novel pattern extraction technique of ADCMA.

2. The Deep-learning (DL)technique was utilized for the classification process of image texture pattern-based feature analysis.

3. Enhancing the classification performance by validating the image pattern in various angles of projections.

4. To form a robust model of object identification system that can be useful for any kind of applications.

The descriptions about the proposed paper work can be organized by the following segmented titles: the section II presented a survey list to describe about the feature extraction and classification model for object identification. The section III explains about the detailed steps of proposed ADCMA feature extraction and other modules. The section IV presented comparative analysis of proposed work with existing object identification system by evaluating the statistical parameters. Finally, the conclusion of advance CMA based object identification system with the future enhancement were discussed and justified in section V.

2. Related Work

This section surveys the various types of image feature extraction methods and to classify the image categories. The major topics that are discussed in the survey is based on the texture pattern extraction models and classification methods in the endoscopic and in other image processing applications.

Initially, the texture pattern extract needs to focus for analyzing the different structure and its characteristics of feature extraction. By considering the work [1] proposed is for texture classification for an image using a noise-invariant-structure-pattern (NISP). The main application of above work is in image retrieval process. The two different pattern such as Global-structure-Pattern and Noise-invariant-Local-structure Pattern was integrated in this work. Similarly, in [2], author fused different pattern extraction methods for feature retrieving. These can be listed as the neighbordifference-pattern (NDP), segmented-structure-pattern (SSP) and the refined LBP (RLBP) for texture classification. Then to enhance the texture classification in the application of underwater image classification, [3] proposed segmentation and texture classification to retrieve the foreground. For the multi-class image recognition, [4] proposed an optimal texture feature extraction method with Deep Neural Network based classification process. This type of texture classification is better for the application of evolving languages for the 1-D image pattern. In [5], this type of language classification for the input images that contains the character set can be evaluate by three different process such as (i) script coding, (ii) texture analysis, and (iii) GAICDA+ clustering. In [6], author proposed an insensitive method of texture analysis for saliency detection. Also, in [7], an effective Local Binary Pattern (LBP) with the spatial info of the image. In this, the bilateral filter based Gaussian coefficients were utilized to form a multi-scale image analysis. The texture pattern was also used for the application of image stegno-analysis-based on the Local-Texture-Pattern (LTP) in [8]. In [9], author proposed novel texture pattern classification model was implemented by using the Weibull distribution (WD) method which randomly-distributed local homogeneous fragments. This pattern classification can be performed by using partial-least-squares-discriminant-analysis (PLS-DA)-based classifier. A real-time image classification grounded on the texture feature extraction for the methods of LPQ and BSIF were survived in [10]. In [11], the paper presented a geometrical invariant texture, shape and color features by means of the methods of multi-channel ZMs (MZMs), Zernike moments (ZMs), color histograms (CH), rotation-invariants of the QZMs (RQZMs) and quaternion ZMs (QZMs). In [12], author proposed a novel LBP pattern extraction for rotation, illumination and scale invariance features which are classified as multi-kernel SVM.

3. Proposed Work

This research work proposed a new model of image texture-pattern-based object identification system. This proposed work performs a grid-based pattern extraction enhanced the feature prediction by multiple angles of pixel boundary estimation. To improve the pixel value of input image for accurate pattern extraction the particular objects was considered for the classification process. These selected objects were pre-processed by the Cellular Automata of filtering method. In this classification module, DL was executed to perform supervised knowledge model which was trained by the histogram feature vector of CMA image pattern. Compare to the traditional image pattern extraction methods, the proposed advance CMA method identifies the relationship between neighborhood pixels in a cell which can connect to next cell of the patch. This forms the better prediction of image pattern that enhanced model of LTrP method.

3.1 The main intension of the proposed analysis

1. The Laplacian-based image-transformation with Cellular Automata applied smoothness to reduce the noisy pixels in the sample image and improved the pixel value of the input sample image.

2. The proposed method for extraction of pattern improved the texture analysis by validating the magnitude of multiple neighborhood pixels.

3. The texture pattern provides the depth of image other than the traditional convolution to the image matrix with optimal feature extraction.

4. The deep neural network model presented in the texture analysis will enhance the classification performance in object identification.

Different module of approach that is used for proposed method,

Step1- PP-Preprocessing

Step2- texture pattern (TP using ADCMA)

Step3- classifier using deep learning

Step 1- PP-Preprocessing

First step of the proposed work is preprocessing stage used to improve the pixel scope. [13, 14, 15, 16]. This can be identified by referring the nearest pixels that can be compare with the centroid pixel that was indexed by the mask [17, 18, 19]. The mask that was consider in the filter is to map the cells and validate the pixel value to normalize it.

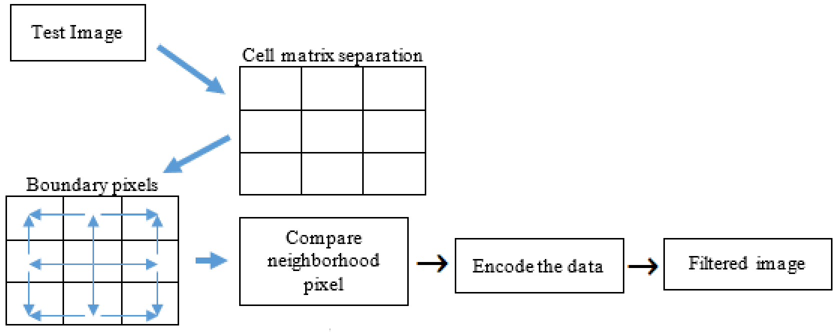
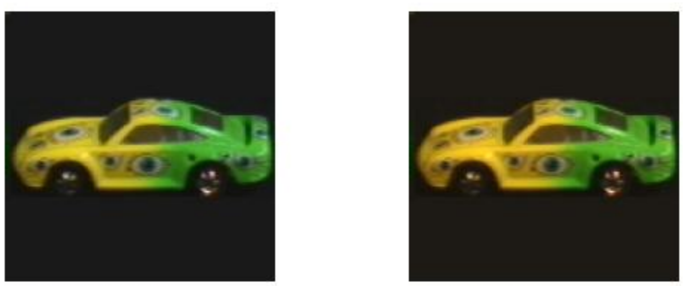


Figure 1. Flow diagram of Image filtering.

The figure 3 shows the example of image filtering process using a sample matrix including its index labelling of the mask. So initially the entire image was changed over into different cells sizes. So based on the size of cell's the size of matrix can be 3×3 and 5×5. As per patterns as the size of cell or mask will reduces the execution of filtering process will increased. Thus, in this paper, 3×3 matrix size was used for the filtering process. This will improve the PSNR value for an image that represents higher pixel reconstruction with reduced number of noisy pixels. The flow diagram of CA for the input image is shown in figure 1. In this the image was filtered into cells or matrix to validate its adjoining pixels. From the nearest pixels validation result, this will form as a set of binary streams and then encode to get the normalized pixels. Figure 2 displays the outcome of CA algorithm for filtering of COIL-100 dataset input image. From this result, the image gets enhanced with normalized image and smoothened that are compare from the original input image.



(a) Input Image (b) Filtered

Figure 2. Outcome of CA algorithm for filtration of COIL-100 dataset image.

B. Step-2- Texture-Pattern-Extraction (TPE)-ADCMA

The stepwise description of algorithm is presented in this section

Algorithm 1. texture-pattern-algorithm- Advance CMA

Input: COIL-100 dataset Image, P

// sample image dataset is COIL-100

Output: P_P- Image Texture Pattern

Step1. For gaussian distribution calculate the filter coefficient. After convolution padding image is known as M and zero padding in image 2*2 at boundary.

Step 2. Initialization of matrix P_m is used to calculate the value of mask

For t=3 to m-2 t-represent horizontal

For r=3 to n-2 r-represent vertical

$P_m = M(t-2 : t+2,\ r-2 : r+2)$

$P_c = M(t, r)$ //center value.

Step 3. Bi=0

// Bi is binary weight

For k=1 to 8.

Loop

Gather the plan of neighborhoods 'a_k' from equation (5)

Where, $i = 2$ top-1

$j = 2$ toq-1

find 'μ_k' for every loop of 'k' from condition (6).

find 'μ_k' for each 'a_k' from condition (7).

Calculate the sign changes z from center pixel to boundary pixel equation 8 gives the binary value 'Bi' for different value of 'z' by equation (9).

End circle 'k'

$$P_m(t-2,, r-2) = B_i$$

End circle 'r'

End circle 't'

The algorithm 1 clarifies about the progression strategy of proposed CMA design extraction technique and its conditions. The detailed depiction can be clarified in the accompanying assertions.

Using 5×5 input image P_k. The CMA equation (1).

$$M(t, r) = G(t, r, \sigma) * P(t, r) \tag{1}$$

Where, $G(t, r, \sigma)$ //Gaussian coefficient value

By using eq. (2) calculate gaussian value

$$G(t, r, \sigma) = \frac{1}{2\pi\sigma^2} e^{\frac{t^2+r^2}{2\sigma^2}} \text{ // } \sigma \text{ filter standard deviation}$$

Spatial value of coordinate represent as t, r (2)

To assess the inclination of the tangled picture, this can be addressed by greatness $(| G_{xy} |)$ and slope $(\alpha(x, y))$ of the tangled network. The size and period of tangled picture can be assessed as in equation (3).

$$| G_{tr} | = \sqrt{G_t^2 + G_r^2}, \alpha(t, r) = \tan^{-1}\left(\frac{G_t}{G_r}\right) \tag{3}$$

Where, 't' and 'r' present the cell size

$$G_t = \frac{\partial C_i}{\partial t} \text{ and } G_t = \frac{\partial C_I}{\partial r} \tag{4}$$

These slope for the angles of $\{+ 90^\circ, + 45^\circ, 0^\circ, - 45^\circ\}$.

From this, the arrangement of neighborhood pixels can be removed as a_k which is addressed as in equation (5)

$$\alpha_k = P_m(t-1, r-1) \tag{5}$$

For every cycle we calculate μ_k This can be assessed by the equation (6).

$$\mu_c = \frac{1}{8}\sum_{a=1}^{8}\frac{|a_k(a) - P_M(i, j)|}{l_M(i, j)} \quad \text{// mean pixel value} \tag{6}$$

Also we calculate center pixel values in equation (7). This can be represented as 'μ_c'.

$$\mu_c = \frac{1}{8}\sum_{a=1}^{8}\frac{|a_k(a) - p_c|}{p_c} \quad \text{// center pixel} \tag{7}$$

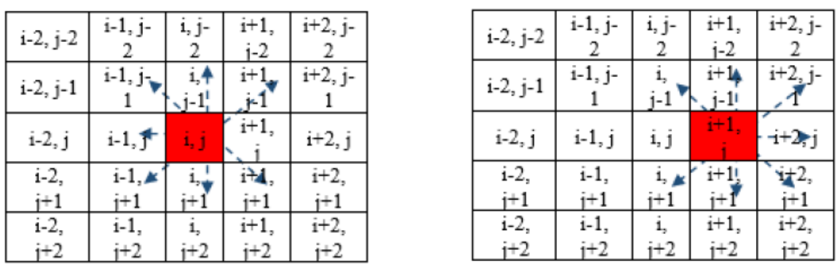
From calculate z value for every cycle of 'k',

$$z = \begin{cases} 1, & if\ (\mu_k > \mu_c) \\ 0, & \text{Otherwise} \end{cases} \tag{8}$$

From binary stream, the comparing decimal worth 'Bi' can be determined as in equation (9).

$$B_i = B_i + (2^{(k-1)} \times z) \tag{9}$$

here, the 'B' is instated as nun for every cycle of 't' and 'r'.



(a) Estimate α_c (b) Estimate α_k

Figure 3. Schematic Structure of CA mask.

Figure 3 red mark pixel calculate from ADCMA for parameter 'α' and value of middle value of pixel refer a_c. The 'a_k' calculated at different angle. In that, the arrow indicates the projection angles that are referred to estimate the magnitude of current matrix. Here, it will not consider the center pixel for 'a_k' and the boundary pixel will not be considered for 'a_c'.

This pattern extraction method also follows the mask window as same like the matrix representation that is use in the filtering method. The sample model of mask selection in 5×5 size is represented in figure 2(b). In the proposed CMA method, it extracts the patterns as per numerous angles of projection plane such as $\{+90^{\circ}, +45^{\circ}, 00, -45^{\circ}\}$. The figure 4 displays the output for the filtered image of CMA texture pattern analysis.

Figure 4. Texture pattern of CMA result.

Step 3. Texture Classification

The standard of the consistency extraction is to improve the object identification issue by assessing the weight of every neuron and fortify the organization layer availability in the dynamic scope of choosing the neurons for the proposed object identification with DNN classifier [20, 21, 22, 24].

Classifiers are that can be ordered as two distinct models like multi-labels and binary labels. Bi is used for image pattern class 0 or 1. The multi-classifiers that are can be used to classify the image types that are in multiple number of labelled images. Also, for the image texture pattern classification, the Deep learning model was used to perform enhanced accuracy that by using the traditional pattern analysis methods [23, 25, 29].

4. Result Analysis

The overall work was tested in the different types of image dataset that are considered to present a dynamic range of image classification. A dataset of COIL-100 images multiple object identification dataset used with different pattern identification method. This dataset is to validate the proposed work for multiple object combination. Since the proposed work is applicable for any type of object identification datasets. To prove that, some generic images were utilized for the training and then testing of objects from the dataset. Also, the proposed work was tested with the face recognition dataset to justify the performance of pattern extraction method with adversarial attacks. [30, 31]

These can measure up to the proposed work by utilizing the parameters, for example, Specificity, Sensitivity, Jaccard, Precision, Dice Overlap, Recall, Matthew's relationship coefficient (MCC), F1-Score, Accuracy and Error rate Kappa Coefficient.

From this value, the presentation of proposed work is addressed by utilizing the concept of confusion matrix. Usage of confusion matrix for the COIL dataset is introduced in the table 1 for the sample dataset of 317 pictures of item 1 objects and 290 pictures of item 2 objects.

Table 1. Confusion matrix of proposed work for COIL image dataset.

Actual \ Predicted	Item1	Item2
Item1	311	6
Item2	6	289

Table 2. Performance analysis parameters of proposed extraction method for COIL-100 image dataset.

Parameters	Values
Specificity	0.98017
Sensitivity	0.97696
Jaccard Similarity	0.96013
Dice Overlap	0.98035
Precision	0.97966
Recall	0. 97966
F1-Score	0.97966
Accuracy	0.98034
Kappa Coefficient	0.96043
Error Rate	0.01961

MCC	0.96703

In figure 8 the comparison analysis of the proposed work with the existing LBP based-texture extraction method based on performance is presented. Also, the figure 6 represents the amount of error rate that are reduced by the proposed CMA method which was compared with the LBP. The bar charts in these figures exports the parameters of Sensitivity, Precision, Specificity, MCC, F1-Score and the Error rate with False Rejection Rate (FRR) for the proposed CMA with DL based classification that are estimated by validating the classification result with basic truth of the image dataset. From this analysis, it explains that the proposed work achieved ~98% of accuracy.

The figure 5 and 6 displays the examination bar analysis for the values of Receiver Operating Curve (ROC), Kappa Coefficient and Accuracy from the consequence of customary LBP and planned CMA techniques that are verified in complete dataset. In this, the ROC curve is plotted for the parameters of True Positive Rate vs False Positive Rate. The False Positive Rate can be estimated by subtraction of Specificity from the value 'one' and the TPR represents the Sensitivity. This shows that the curve reaches the maximum sensitivity value while at the duration of minimum FPR value that represents the overall false rate of proposed work is a lesser amount of in the range of ~0.2.

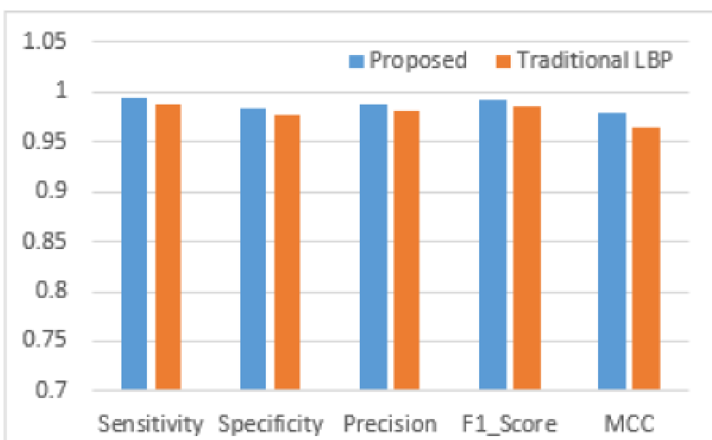


Figure 5. Performance Measures.

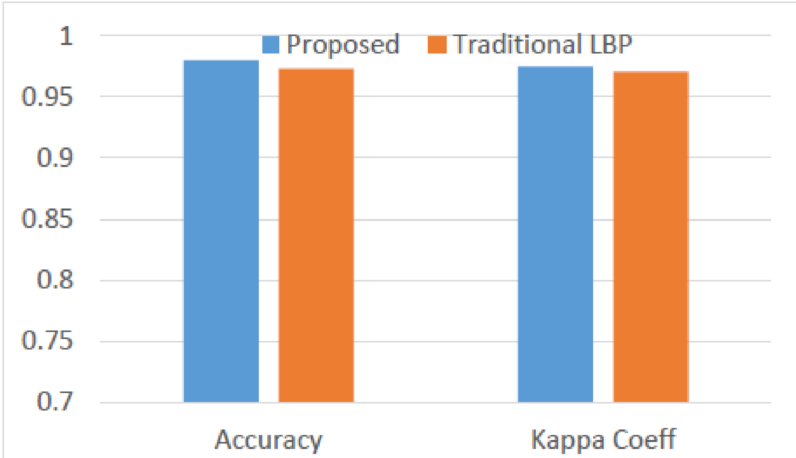


Figure 6. Accuracy chart.

The comparisons of proposed work for analyzed parameters such as Precision, Average Recognition Rate (%), and Recall with the existing methods in [25] is shown in table 3. The comparison analysis of proposed work with other existing algorithm [26] is represented in table 4 for the attack threshold value '5'. In figure 7a bar chart analysis displays the assessment of proposed result with work of [27]. This analysis is done based on the accuracy parameterforCOIL-100 image data set. This figure shows that the proposed ADCMA strategy improved the presentation than the existing of feature extraction technique.

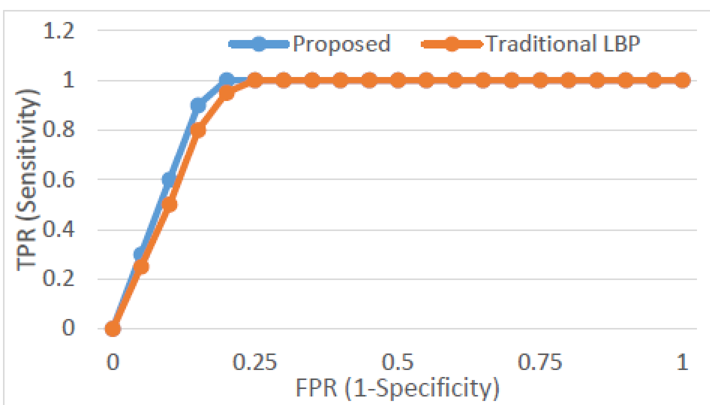


Figure 7. ROC Curve.

Table 3. Average Recognition Rate (ARR), Precision and Recall Comparison with [25].

Methods	ARR (%)	Precision	Recall
OIM (1)	85.51	0.83	0.84
OIM (2)	90	0.88	0.89
OIM (3)	95.01	0.94	0.93
MORSCMIs	90	0.89	0.9
QRSCMIs	85.5	0.84	0.84
Traditional LBP	83.2	0.83	0.82
Proposed	97.6	0.96	0.95

Table 4. Comparison analysis of proposed work with other existing algorithm for the attack threshold value '5'.

Classification Methods	AUC
Proposed	0.928
MLP + L2	0.967
LSTM + cos	0.927
LSTM + L2	0.996
MLP + cos	0.951

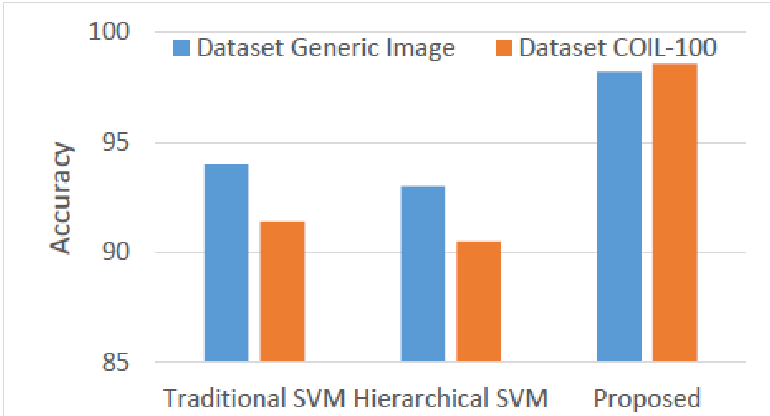


Figure 8. Comparison chart for accuracy factor for classification of image.

The table 3 shows the comparison for accuracy factor for classification of the COIL-100 image dataset. The result of comparison for proposed work is with the method in [28]. Since, the deep learning method achieves high accuracy rate in both the classification process.

These results data and its analysis report shows that the proposed method of pattern extraction with novel texture pattern extraction model achieved better performance level and the similarity measures than the other machine learning methods.

5. Conclusions

This research work proposed a new method of feature analysis for the texture cataloging of anomaly class for the usage of object identification. In this work, the proposed ADCMA executed better compared to the conventional technique for feature extraction classification model. The anomaly of the image was assessed by utilizing the Deep Learning classifier. As per the result analysis, it characterizes that the proposed pattern-extraction approach accomplished high execution rate while contrasting different strategies. The block-separation-based image pattern extraction by the proposed DL and ADCMA delivers the accurate organization aldesign of input image. In that, the Deep Learning additionally worked on the exhibition of classification that includes block-based machine-learning way to deal with analysis the element vector of image pattern to recognize the irregularity class. From the result of this model, the recognition rate gives ~98% better than the other object extraction strategy.

For future work, pattern-based classification can be implemented in the different types of medical image dataset to increase the classification rate and also improve the performance rate furthermore. For the pattern extraction process, the accuracy rate can be improved by the optimal selection of window size of ADCMA and with different angle projection.

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