MEDICAL IMAGE CLASSIFICATION USING SPATIAL ADJACENT HISTOGRAM BASED ON ADAPTIVE LOCAL BINARY PATTERNS

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In fulfillment for the course of

Image Processing (CSE4019)

School of Computer Science and Engineering

VIT
UNIVERSITY
(Estd. u/s 3 of UGC Act 1956)
VELLORE ■ CHENNAI
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DECLARATION

I hereby declare that the project entitled "MEDICAL IMAGE CLASSIFICATION USING SPATIAL ADJACENT HISTOGRAM BASED ON ADAPTIVE LOCAL BINARY PATTERNS" submitted by us to the School of Computer Science and Engineering, VIT University, Vellore in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Computer Science and Engineering is a record of bonafide work carried out by us under the supervision of Prof. Rajumar S. I further declare that the work reported in this project has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma of this institute or of any other institute or university.

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CERTIFICATE

The project report entitled "MEDICAL IMAGE CLASSIFICATION USING SPATIAL ADJACENT HISTOGRAM BASED ON ADAPTIVE LOCAL BINARY PATTERNS" is prepared by Utkarsh Sharma (Registration No: 16BCE0226), Mahima Singh (Registration No: 16BCI0076), Subhrajit Jana (Registration No: 16BCB0087) and Harsh Pratap Singh (Registration No.: 16BCE0299). It has been found satisfactory in terms of scope, quality and presentation as partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Computer Science and Engineering in VIT University, India.

Prof. Rajkumar S

ACKOWLEDGEMENT

I would like to express my gratitude to all those who have helped me in the successful completion of this project. Without their support, I would not have been able to achieve the goal of the project successfully.

I would like to take this opportunity to thank our guide, Prof. Rajkumar S, for his constant support, guidance and mentorship without whom it would have been really difficult to complete the project on time.

Furthermore, I would also like to acknowledge with much appreciation, the important role of Dr. Santhi V., Head of the Department, SCOPE, whose contribution in encouragement helped me plan better.

I would like to thank our Dean, Dr. Saravanan R., who provided me with the facilities required and conducive conditions for the project.

Finally, I would like to express my sincere gratitude to VIT University, which provided me with a platform to hone my skills.

1. ABSTRACT:

The recognition of medical images is an important task both in the computational vision and in computational biology. In the field of medical image classification, the representation of an image based on the local binary pattern descriptor (LBP) has become popular. However, most existing LBP-based methods encode binary models in a fixed proximity range and ignore spatial relationships between local models. The omission of spatial relationships in the LBP will cause poor performance in the process of acquiring discriminatory characteristics for complex samples, such as medical images obtained with a microscope. To address this problem, in this paper we propose a new method to improve local binary models by assigning an adaptive range of adaptation for each pixel. Based on these adaptive local binary patterns, we also propose an adjacent strategy for the spatial histogram to encode the microstructures for the representation of the image. A wide range of evaluations is performed on four sets of medical data showing that the proposed method significantly improves the LBP standard and compares favorably with other prevalent approaches.

2. INTRODUCTION:

Medical images have played an important role in the diagnosis of patients. Automated classification of medical images is a desirable tool for assigning image interpretation, and therefore would help the expert in diagnosing diseases. In terms of features used for the recognition of medical images, it can be classified mainly into three groups: shape, color and texture characteristics. The characteristics of the form, such as the momentary invariants and the Fourier descriptor, are used to classify medical X-ray images. It is considered a vector color field to improve the performance of the classification of endoscopic images. Local binary patterns are widely regarded as a descriptor of cutting-edge image functionality among texture descriptors, since they can more effectively describe frame information. It has been successfully applied in many applications, such as facial recognition, textural classification, scene recognition, detection of people and more. LBP has many interesting advantages: it has proved to be a powerful discriminator with a low computational cost, it is resistant to changes in the intensity of the image and can be easily implemented. Because of these merits, it is a good option to extract the fine features for medical images. The idea behind LBP is that it describes an image according to local schemes. It has been found that existing methods improve LBP to a certain extent by reconfiguring or using patterns. However, most existing jobs encode binary models within a fixed neighborhood radius. This fixed neighborhood radius strategy is irrelevant to local image content and disregards microstructure information of the multi-scale patterns. Intuitively, the micro-structures, i.e. the spatial relationships among local patterns generated by adaptive radius, provide crucial feedback in disambiguating texture information especially for complex medical images, i.e. microscope images that involve with pathological changes. This subsequently leads to improved recognition performance. . In the first stage, with the help of gradient operators, we obtain a gradient map from each original image, and the adaptive LBP neighborhood radius could be then determined for each pixel by utilizing the gradient information. As a result, our adaptive strategy will assign a relatively small radius to pixels that are located in local regions with dramatic gray variation, while assigning a relatively large radius to pixels that are located in local regions with slight gray variation. This adaptive technique will provide the image with rich micro-structure textures, which is discriminative in image representation. Then in the next stage, we propose a spatial adjacent histogram based on adaptive LBP radius to describe these discriminative micro-structure features. Finally, the adaptive LBP. radius and spatial adjacent histogram strategies produce a much more powerful LBP variant.

In this context, our contribution is:

1) Using the adaptive strategy we proposed, the neighborhood radius of LBP is determined based on local image content.

2) Spatial adjacent histogram to encode the micro-structures produced by adaptive strategy which helps in building the histogram.

3.PROPOSED SCHEME:

In this section, we propose a novel idea using spatial adjacent histogram based on adaptive local binary pattern(SAHLBPT) for medical image classification.

3.1: Brief Review about LBP(local binary pattern):

Given an image I, the LBP is a gray-scale texture operator that characterizes the local spatial patterns of the image texture, which is calculated at each pixel by evaluating the binary differences between it and its neighbors:

$$LBP(P,R) = \sum_{i=0}^{P-1} s(g_i - T)2^i, \quad s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases}$$

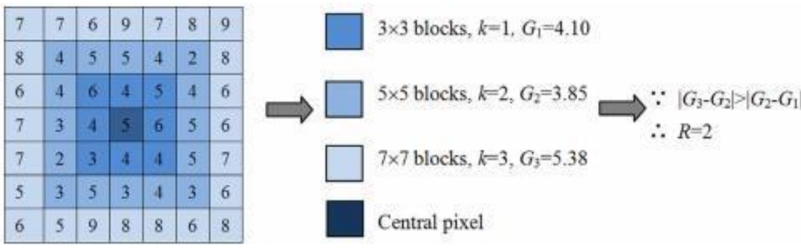
where P is the number of pixels in the neighborhood, R is the radius of the neighborhood and T is a threshold. A pattern is considered uniform if the number of transitions in the sequence between 0 and 1 is less than or equal to two.

3.2: Determining the adaptive radius R:

In order to extract micro-structures of different scales, the key idea behind this paper is to adaptively obtain the LBP radius of each pixel by analyzing the differences based on calculated gradients. Given an image I and we use f(x,y) as the gray value of pixel (x, y), then the Sobel gradient magnitude is used.

$$\begin{cases} g_x = [f(x-1,y+1)+2f(x,y+1)+f(x+1,y+1)] \\ \quad -[f(x-1,y-1)+2f(x,y-1)+f(x+1,y-1)] \\ g_y = [f(x+1,y-1)+2f(x+1,y)+f(x+1,y+1)] \\ \quad -[f(x-1,y-1)+2f(x-1,y)+f(x-1,y+1)] \end{cases}$$

$$g(x,y) = \sqrt{{g_x}^2 + {g_y}^2}$$



Finally, the gray variation is defined as the intensity difference among the average gradients in different sizes of image blocks. Thus, the neighborhood radius Rgc(maximum radius) of the central pixel gc can be obtained. In each adaptive radius map, we take four radius that are R=1, R=2,R=3, and R=4.

3.3. LBP coding schemes based on adaptive radius:

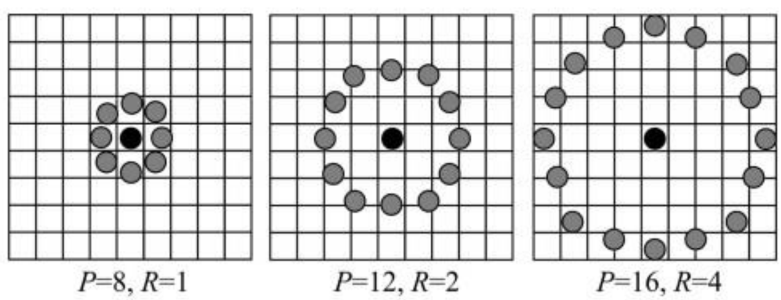
In this subsection, we formulate the process of LBP coding based on adaptive radius R. Given a center pixel gc, the neighborhood radius R is comuted. Inspired by state-ofthe-art LBP coding strategy, three coding schemes are selected based on setting different thresholds to T of adaptively, which are named T1, T2 and T3 for short, respectively. And LBPT1, LBPT2 and LBPT3 denote standard LBPs obtained by the three coding schemes, respectively.

The Fomula is denoted by

Set T3 as the mean gray value of the (2R+1) x (2R+11) image blocks, i.e.

$$T_3 = \sum_{i=1}^{N} g_i / N, \quad N = (2R+1) \times (2R+1)$$

$$LBPT_3 = \sum_{i=0}^{P-1} s(g_i - T_3) 2^i$$



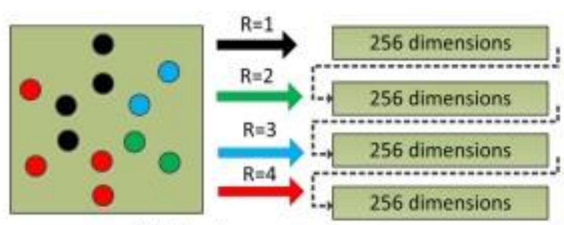
3.4. Spatial adjacent histograms based on adaptive LBP:

As mentioned in subsection 2.2, each pixel of an image has different neighborhood radius during our adaptive strategy, however, different configurations of (P, R) will result in LBPT of each pixel mapping to different dimension. In this paper, we set the number of involved adaptive neighbors as 8, i.e. P=8. Besides, our spatial adjacent histogram encoding strategy will result in the final feature vector with 2 x Rmax x 2p dimensions. This means that increasing the values for P and Rmax will make the feature dimension significantly large, that will further increase the time complexity. Considering the trade-off between description and performance, we set the maximal search radius Rmax as 4. Moreover, increasing Rmax means that more image pixels are involved to interpolate and form neighborhoods with fixed number P=8. This may bring more noise to the interpolated neighborhoods. So we think it is appropriate to set Rmax as 4. Then, four histograms with 256 bins under four radii can be extracted for each image:

$$h(i)\,|\,R_k = \sum_{j \in R_k} isequal(lbp(j) = i), \quad i = 1, \ldots, D; k = 1, \ldots, 4$$

where Rk indicates the set of pixels with radius R=k, and D denotes the dimension of LBP histogram (here D is equal to 256). The function lbp(j) returns the LBP value of pixels j, and the function isequal(lbp(j)=i) returns 1 if lbp(j)=i, else returns 0.

Then for image representation, an easy option is that we directly concatenate the four histograms under the different radii, then the concatenated histogram DCLBP is as follows:

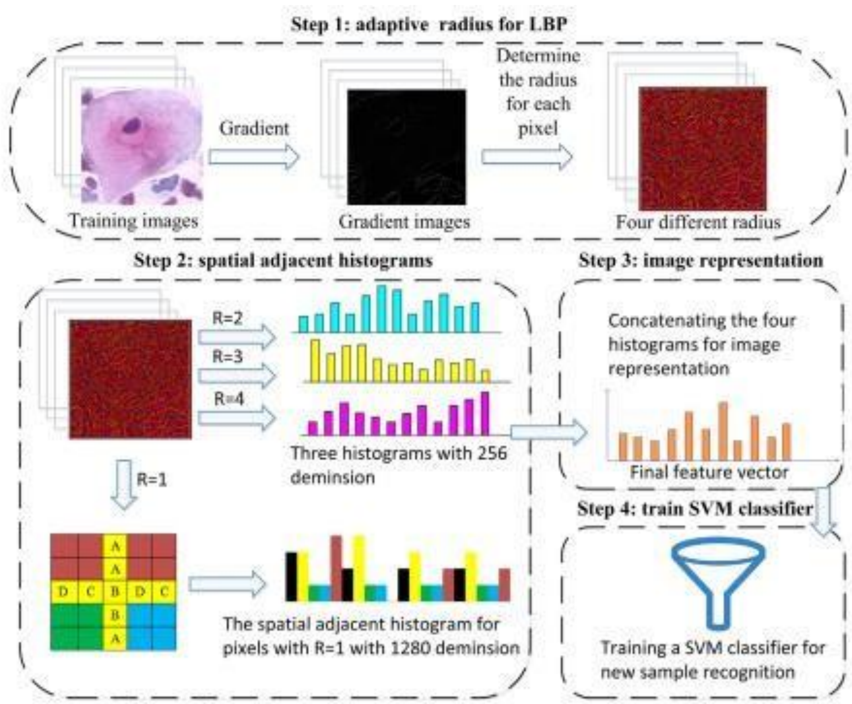


(a) directly concatenate strategy

$$DCLBP^{T_i} = H^{T_i}(R_1)(+)H^{T_i}(R_2)(+)H^{T_i}(R_3)(+$$

3.5. The proposed image classification framework:

The framework for medical image classification consists of four steps, i.e. determining the adaptive LBP radius for each pixel, computing the spatial adjacent histogram based on adaptive LBP radius, representing the image based on the spatial adjacent histograms,



and training a SVM classifier for recognizing new samples. Furthermore, the first three steps can be considered as feature extraction for medical image, which is the key idea of our proposal. Since different classes may have different numbers of samples, we use stratified cross validation instead of standard cross validation to handle this imbalance of image numbers among classes. In stratified cross validation, the distribution of samples among classes in each subset is basically consistent with that in original dataset.

4.EXPERIMENTAL RESULT:

4.1Experimental datasets:

The medical datasets for the evaluation of the proposed method are selected based on their variety and broadness of their use. We used the 2D Hela Dataset. This dataset is composed of 862 single-cell images (16 bit gray scale of size 512 by 382 pixels) from ten classes, i.e. Actin, Nucleus, Endsome, ER, Golgi Giantin, Golgi GPP130, Lysosome, Microtubules, Mitochondria, and Nucleolus.

4.2. Experimental setup and implementation:

We implement the experiments in an iterated random splitting-scheme (consistent among all methods) for training and testing. Each dataset is randomly divided into 80% for training and 20% for testing. We use the training-split to optimize the SVM parameters and train model in a 5-fold cross validation.

4.3.. Evaluation of our methods:

LBPTi with (R=2, P=16) performs better than DCLBPTi. We conjecture that it is because the LBPTi with (R=2, P=16) captures more texture information with very large feature dimension (i.e. 65536 dimensions), while the feature dimension of DCLBPT is 1024. However, the DCLBPTi achieves higher accuracies than LBPTi with both (R=1, P=8) and (R=2, P=8) in most cases. The comparison between the DCLBPTi and LBPTi suggests that the adaptive radius is not very suitable to combine with directly concatenate strategy. We mainly compare the DCLBPTi with SAHLBPTi to show the superiority of adaptive radius combined with spatial adjacent histogram.

4.4. Comparison of the LBP-based methods:

1) LBP-r the standard LBP with rotation invariant.
2) EBP], the elliptical binary pattern variant.
3) LBPsu, scale-adaptive and sub uniform-based rotation invariant LBP.
4) LBPnr], scale-adaptive LBP without rotation invariant, that employs the LBPsu2 approach by using non-rotation invariant instead of rotation invariant.
5) LBP-HF, local binary pattern histogram Fourier features.
6) LDBP, the local difference magnitude binary pattern variant
7) CLBP in which three types of features are combined to form the completed LBP features
8) CoALBP in which the co-occurrence among adjacent LBPs has been considered.

4.5. Runtime Analysis:

The computational time for feature extraction mainly depends on the descriptor and the image size, while the training and testing are mainly dependant on the classifier, feature dimension and the scale of the dataset. Our method has took 0.823 s in the feature extraction stage per image with 512 x 382 size and 6.553 s in the training stage for 862 samples with 3072 feature dimensions. We think that our computational demand is an adequate trade-off. Viewed from this perspective, we believe our method can be extended to large-scale datasets. The BoVW model using the multiple features, i.e. SIFT+ SAHLBPT3, excels that using a single feature on PAP, 2D-Hela, and Tumor datasets based on the accuracy and the macroaveraged F1 score. However, the SAHLBPT3 works better than SIFT+ SAHLBPT3 on 2D Hela dataset, which means that SIFT and SAHLBPT3 descriptors.

5. OUTPUT:

Dataset:

Shared Folder

Name	Date Modified	Size	Kind
DATASET	Yesterday at 2:02 AM	--	Folder
ActinFilaments	Yesterday at 2:07 PM	--	Folder
Endosome	08-Oct-2018 at 11:41 AM	--	Folder
ER	08-Oct-2018 at 11:41 AM	--	Folder
Golgi_gia	08-Oct-2018 at 11:41 AM	--	Folder
Golgi_gpp	08-Oct-2018 at 11:41 AM	--	Folder
Lysosome	Yesterday at 2:11 PM	--	Folder
Microtubules	08-Oct-2018 at 11:41 AM	--	Folder
Mitochondria	08-Oct-2018 at 11:41 AM	--	Folder
Nucleolus	08-Oct-2018 at 11:41 AM	--	Folder
Nucleus	08-Oct-2018 at 11:41 AM	--	Folder
LBP.pdf	09-Oct-2018 at 1:58 PM	6.9 MB	PDF Document
SIFT+LBP.ipynb	Yesterday at 3:14 PM	8 KB	Document

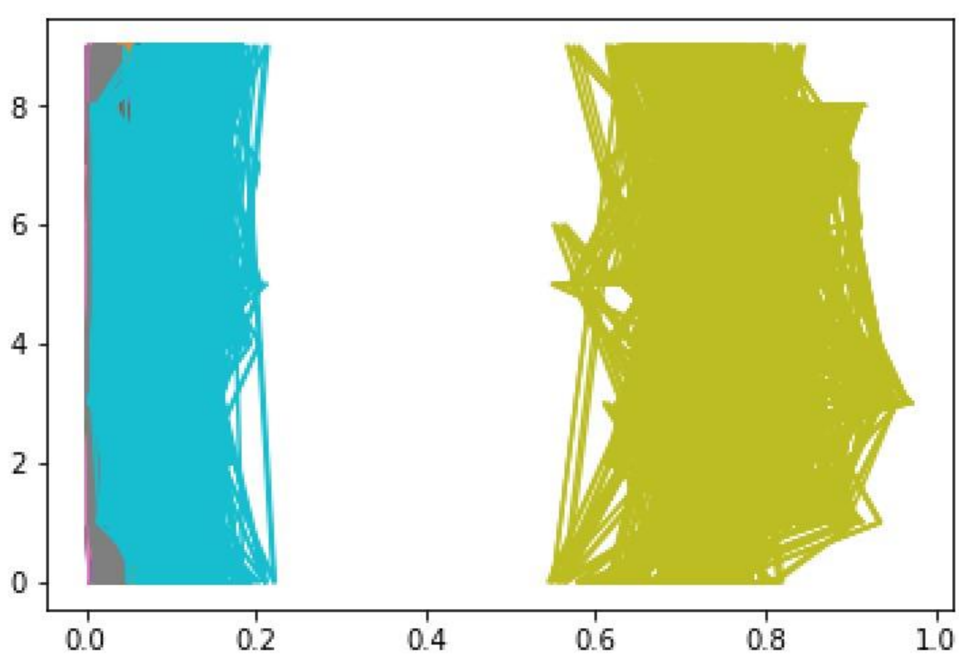
Test Dataset:

testData	Yesterday at 2:11 PM	--	Folder
0.png	11-Apr-2001 at 12:45 AM	59 KB	PNG image
1.png	11-Apr-2001 at 12:45 AM	97 KB	PNG image
2.png	11-Apr-2001 at 12:44 AM	56 KB	PNG image
3.png	11-Apr-2001 at 12:44 AM	29 KB	PNG image
4.png	11-Apr-2001 at 12:45 AM	33 KB	PNG image
5.png	11-Apr-2001 at 12:45 AM	71 KB	PNG image
6.png	11-Apr-2001 at 12:45 AM	57 KB	PNG image
7.png	11-Apr-2001 at 12:45 AM	64 KB	PNG image
8.png	11-Apr-2001 at 12:45 AM	52 KB	PNG image
9.png	11-Apr-2001 at 12:44 AM	52 KB	PNG image
testSIFT.png	10-Apr-2001 at 9:39 PM	67 KB	PNG image

Training:

```
/Users/shreyashkawalkar/Developer/LBP SIFT/texture-matching-master/perform-training.py:100: DeprecationWarning: `itemfreq`
is deprecated!
`itemfreq` is deprecated and will be removed in a future version. Use instead `np.unique(..., return_counts=True)`
  x = itemfreq(lbp4.ravel())
r30jun97.mc151.15--1---2.dat.png (382, 512, 3)
r13feb98.mc151.33--1---2.dat.png (382, 512, 3)
r13feb98.mc151.26--1---2.dat.png (382, 512, 3)
r06aug97.mc151.15--1---2.dat.png (382, 512, 3)
r13feb98.mc151.29--1---2.dat.png (382, 512, 3)
r13feb98.mc151.21--1---2.dat.png (382, 512, 3)
r13feb98.mc151.34--1---2.dat.png (382, 512, 3)
r30jun97.mc151.07--1---2.dat.png (382, 512, 3)
r06aug97.mc151.07--1---2.dat.png (382, 512, 3)
r06aug97.mc151.12--1---2.dat.png (382, 512, 3)
r30jun97.mc151.13--1---2.dat.png (382, 512, 3)
r30jun97.mc151.06--1---2.dat.png (382, 512, 3)
r13feb98.mc151.20--1---2.dat.png (382, 512, 3)
r06aug97.mc151.13--1---2.dat.png (382, 512, 3)
r06aug97.mc151.06--1---2.dat.png (382, 512, 3)
r13feb98.mc151.28--1---2.dat.png (382, 512, 3)
r13feb98.mc151.27--1---2.dat.png (382, 512, 3)
r13feb98.mc151.32--1---2.dat.png (382, 512, 3)
r30jun97.mc151.01--1---2.dat.png (382, 512, 3)
r30jun97.mc151.14--1---2.dat.png (382, 512, 3)
r06aug97.mc151.01--1---2.dat.png (382, 512, 3)
r06aug97.mc151.14--1---2.dat.png (382, 512, 3)
r06aug97.mc151.09--1---2.dat.png (382, 512, 3)
r30jun97.mc151.09--1---2.dat.png (382, 512, 3)
r06aug97.mc151.03--1---2.dat.png (382, 512, 3)
r06aug97.mc151.16--1---2.dat.png (382, 512, 3)
r30jun97.mc151.03--1---2.dat.png (382, 512, 3)
r30jun97.mc151.16--1---2.dat.png (382, 512, 3)
r13feb98.mc151.25--1---2.dat.png (382, 512, 3)
r13feb98.mc151.30--1---2.dat.png (382, 512, 3)
r06aug97.mc151.11--1---2.dat.png (382, 512, 3)
r06aug97.mc151.04--1---2.dat.png (382, 512, 3)
r13feb98.mc151.22--1---2.dat.png (382, 512, 3)
r30jun97.mc151.11--1---2.dat.png (382, 512, 3)
r30jun97.mc151.04--1---2.dat.png (382, 512, 3)
r30jun97.mc151.19--1---2.dat.png (382, 512, 3)
r30jun97.mc151.18--1---2.dat.png (382, 512, 3)
```

Classification:



Prediction:

```
predicting
3
3.png
(382, 512, 3)
predicting
3
1.png
(382, 512, 3)
```

6. CONCLUSION:

In this project, we have proposed a new framework based on our adaptive local binary adapters.
Models and adjacent spatial histogram for the classification of medical images. First we use the gradient operator to determine the adaptive range of each pixel. Thus, three encoding schemes based on adaptive radius were introduced to process the LBP histograms. To capture the discriminating characteristics of the microstructures produced by the adaptive beam, we proposed to use adjacent spaces
Histogram strategy for image representation. Finally, an SVM classifier is learned. For the task of classification of medical images, we also evaluated four SVM cores in our algorithm to improve its classification power. Based on the experiments conducted in 2D-Hela, we can conclude that our proposed method has achieved better results performance compared to other LBP-based approaches.
Despite the accuracy achieved, there are still some problems open in our framework.
(1) The size of our model is much larger than that of the standard LBP.
which will lead to an increase in calculation time. Feature selection techniques could be used to solve this problem.
2) In the project, we focus LBP in terms of coding of the microstructural characteristics
And we do not design models with invariant rotation. However, rotation invariants are expected to further improve the performance of our model.