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Image Pattern Analysis Using Local Binary Pattern and Histogram Orient Gradient Methodology and Classification using K-NN

Sunanda[1*], Arun Biradar[2]

[1,2] Department of CSE, East West Institute of Technology, Bangalore, India.

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Abstract— Characterization of texture images with various orientation, brightness and scale changes is a difficult issue in Computer vision. This venture proposes two descriptors and utilizations them together to satisfy such assignment for example Histogram Orient Gradient-Local Binary Pattern(HOG-LBP) include extraction. The proposed framework comprises of pretreatment, highlight extraction and grouping. Initial, a HOG-LBP highlight descriptor is proposed to speak to multi-scale, multi-edge signal data. The HOG segment gives the gesture edge gradient information and the LBP gives the texture feature data, which can adjust for the absence of revolution invariance of a solitary element and improve the acknowledgment rate of motions at different scales and numerous edges. At long last, the K-NN classifier is used to understand the image characterization. Trial results on the Brodatz informational collections demonstrate that the proposed strategy can accomplish best accuracy than the other metods. Investigations on the Brodatz database likewise exhibit the execution of the proposed strategy, on the first picture apply create LBP and HOG. Also, log-polar (LP) change is connected on the first picture, and the energies of coefficients on detail sub groups of the log-polar picture these are taken as worldwide texture highlights. We meld the two sorts of highlights for texture order, and the exploratory outcomes on benchmark datasets demonstrate that our proposed technique can accomplish preferable execution over other cutting edge strategies.

Keywords— orientation, HOG-LBP, K-NN, Brodatz, cutting edge

I. Introduction

Order of texture image with various orientation, light and scale changes is a difficult issue in Computer vision and example acknowledgment. This undertaking proposes two descriptors and utilizations them mutually to satisfy such errand for example in view of HOG-LBP include extraction. The proposed motion acknowledgment framework comprises of pretreatment, highlight extraction and grouping. Initial, a HOG-LBP include descriptor is proposed to speak to multi-scale multi-edge signal data. The HOG part gives the signal edge slope data and the LBP segment gives the texture element data, which can adjust for the absence of revolution invariance of a solitary component and improve the acknowledgment rate of motions at different scales and various edges. At long last, the K-NN classifier is used to understand the motion characterization. Test results on the Brodatz informational indexes demonstrate that the proposed strategy can accomplish 99.01% acknowledgment rate. Analyses on the Brodatz database likewise show the execution of the proposed technique, on the first picture apply create neighborhood twofold examples (LBP) and HOG. In addition, log-polar (LP) change is connected on the first picture, and the energies of coefficients on detail sub groups of the log-polar picture these are taken as worldwide texture highlights. We intertwine the two sorts of highlights for texture characterization, and the test results on benchmark datasets demonstrate that our proposed strategy can accomplish preferred execution over other best in class techniques.

Local Binary Pattern (LBP) is presented as an incredible neighborhood descriptor with enlightenment and turn invariance. To additionally improve the discriminative intensity of texture descriptor, bunches of LBP variations have been proposed. Heikkila et al. present the middle symmetric nearby paired example (CS-LBP) descriptor for coordinating and article classification order. Rather than contrasting every pixel and the inside pixel, CS-LBP looks at focus symmetric sets of pixels in order to lessen the histogram length of LBP. The texture descriptor has all the earmarks of being progressively strong to enlightenment and impediment by joining the great properties of the SIFT and LBP. Liao et al. propose prevailing neighborhood paired example (DLBP) for texture characterization. The DLBP technique processes the pivot invariant LBPs and after that sorts them in plunging request. The initial a few most every now and again happening examples are utilized to catch enlightening texture data. Guo et al. build up a finished nearby paired example (CLBP) conspire, which incorporates administrators of CLBP-Center, CLBP-Sign and CLBP-Magnitude. While joining the three highlights for turn invariant texture arrangement, noteworthy execution improvement can be accomplished.,

II. RELATED WORK

Texture interaction is generally utilized as one of the normal techniques, vision-based motion acknowledgment innovation is additionally an examination hotspot. The general procedure of vision-based signal acknowledgment incorporates picture preprocessing, include extraction and order. One of the difficulties in signal acknowledgment is the way to extricate the most distinctive highlights from the multi-scale and multi-edge motion pictures, and how to choose a fitting classifier. The broadly utilized 2D highlights incorporate LBP[6], Krawtchouk [13], HOG [10], HOG-HOF [12], and geometric highlights [12], which for the most part execution great. Ding et al. [17] separated the highlights of Gaussian obscured pictures and salt and pepper noised pictures by utilizing the course strategy for HOG and LBP, and utilized the asboosting classifier to order extraordinary motion pictures. Gao et al. [6] utilized versatile HOG-LBP highlights to follow palms in shading pictures. In any case, existing HOG-LBP highlights are not extremely powerful for multi-scale and multi-edge object acknowledgment. Particularly when the scale and edge of the motion changes, the acknowledgment rate of the above technique will diminish fundamentally. At present, numerous researchers have completed a great deal of research on multi-scale and multi-edge signal acknowledgment. Kopf[16] and Zhang[17] utilized shape scale space (CSS) to catch the neighborhood highlights of signals. Kelly et al. [19] utilized the element of the size capacity and the Hu minute to speak to motions, where the twofold forms was spoken to by Hu minutes and the size capacity originated from the limit shapes. The Hu minute and the size capacity were consolidated to acknowledge motion acknowledgment. So as to additionally improve the acknowledgment rate of multi-scale and multi-edge motions, a few researchers have proposed some circuitous strategies that initially play out some turn or displaying on the motions, and after that separate highlights. Priyal et al. [9] proposed a turn standardization strategy that used the motion geometry to adjust the removed signals. The motion picture was distinguished through skin shading recognition and sectioned to get a twofold outline. These standardized parallel outlines were spoken to utilizing Krawtchouk minute highlights and arranged utilizing a base separation classifier, which additionally empowers great acknowledgment of few preparing tests. Zhou et al. [10] set forward a novel calculation for a streamlined finger display. The finger state was identified by the parallel idea of finger shapes. The calculation was practically unaffected by the aggravations, for example, hand turn edge changes. Julius et al. [14] proposed a picture division procedure dependent on the angle histogram (HOG) include and utilized SVM[18] to distinguish the flag of the ball arbitrator in the video and the exactness of the framework can achieve 97.5%. It very well may be seen from the current writing that the shape data and texture data are commonly utilized for the signal acknowledgment. Aberrant techniques have likewise accomplished a few outcomes on multi-scale and multi-point motion acknowledgment. In any case, the aberrant technique is effectively influenced by turn and displaying precision, which will build vulnerability of the framework. In addition, it will builds the calculation weight and time cost and will definitely lessen the execution productivity of the framework. Along these lines, it is important to examine an immediate strategy for the element dependent on the scale and point invariance. This paper proposes an improved combination include HOG-LBP[17] that joins cell-organized HOG with 9 uniform examples LBP. The cell-organized HOG can portray complex signal form well. The 9 uniform examples LBP is utilized to separate texture data for complex motions and has great pivot invariance. The new element has rich signal highlights including form highlights and texture highlights, just as great geometric invariance and revolution invariance. Examination results demonstrate that contrasted and other signal acknowledgment techniques, the proposed calculation can accomplish the most astounding acknowledgment rate on the Brodatz informational index.

III. METHODOLOGY

BRODATZ DATASET

The Brodatz's photograph collection is an outstanding benchmark database for assessing texture acknowledgment calculations. It contains 112 texture classes. Each image represents a texture class with size of 640×640 pixels. In experiments, each texture image is first implemented by a normalization process to eliminate the grayscale background effect, and it is subdivided into 5 images per class. From one single image we get 25 sub images totally, Here each image are of 128 x 128 sized image. The Brodatz Album has turned into the accepted standard for assessing texture calculations, with several investigations having been connected to little arrangements of its pictures. For the training images we considered 15 images, that means after dividing or trimming we get 112 x 15 = 1680 training images. For the Testing images we considered 10 images, that means after dividing or trimming we get 112 x 10 = 1120 Testing images. Thusly it has a moderately vast number of classes, and a little number of models for each class. Most texture examinations on grouping, segregation, and division have been kept running on little subsets of test information from the Brodatz Album, ordinarily four to sixteen pictures without a moment's delay. Also, the tried pictures ordinarily show solid homogeneity inside each class as well as visual and semantic uniqueness between classes. Frequently they are all picked to be "microtextures". This examination varies in that it incorporates around a request of size more prominent assortment, including numerous inhomogeneous and vast scale designs. Also, the Brodatz Album has restricted assortment in example scale, revolution, complexity, and point of view. Creating 168 techniques to deal with these changes is basic for acknowledgment in genuine scenes, however can't be tended to with the present Brodatz information except if it is adjusted. In any case, the present database is essentially more various than has been considered in earlier texture investigation examines. Subsequently, it gives a significant benchmark to assessing progress in texture acknowledgment. The initial thirty texture pictures in the Brodatz collection is shown in figure 1

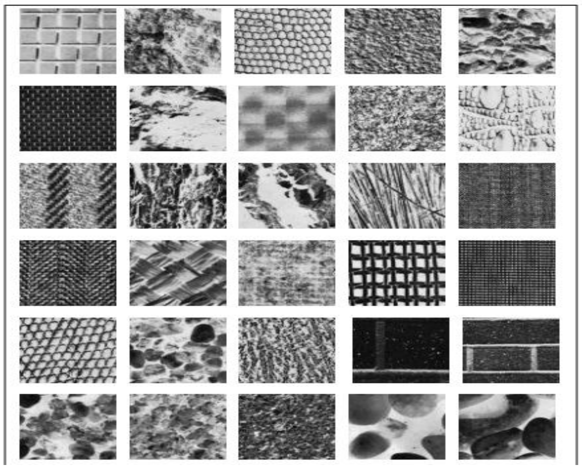

Figure 1. *Example of Brodatz dataset*

LOCAL BINARY PATTERN(LBP)

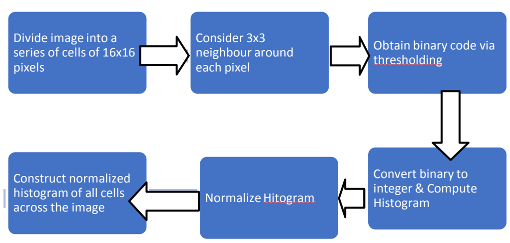

Figure 2. *Feature extraction Steps of LBP*

Local binary patterns (LBP) are a type of feature used for classification in computer vision. LBP is the particular case of the Texture Spectrum model proposed in 1990. LBP was first described in 1994. It has since been found to be a powerful feature for texture classification. LBPs are usually extracted in a circularly symmetric neighborhood by comparing each image pixel with its neighborhood.

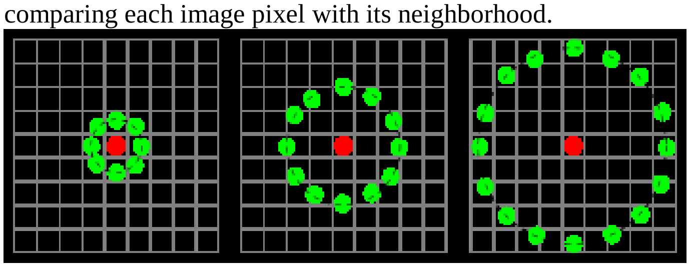

Figure 3. *LBP Calculation for three different neighbors*

The LBP feature vector, in its simplest form, is created in the following also showed in figure 2.

- Divide the examined window into cells (e.g. 16x16 pixels for each cell).
- For each pixel in a cell, compare the pixel to each of its 8neighbors (on its left-top, left-middle, left-bottom, right top, etc.). Follow the pixels along a circle, i.e. clockwise or counter-clockwise.
- Where the center pixel's value is greater than the neighbor's value, write "1". Otherwise, write "0". This gives an 8-digitbinary number (which is usually converted to decimal for convenience).
- Compute the histogram, over the cell, of the frequency of each "number" occurring (i.e., each combination of which pixels are smaller and which are greater than the center).

HISTOGRAM ORIENT GRADIENT(HOG)

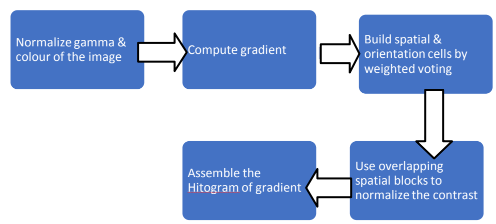

Figure 4. Feature extraction Steps of HOG

The initial phase in HOG include extraction includes processing the slope esteems by applying 1D focused point discrete subsidiary cover in both vertical and flat headings. In particular, this methodology includes sifting the dim scale picture with the accompanying channel pieces, same is showed in figure 4.

$D_x = [-1\ 0\ 1]$ and $D_y = [-1\ 0\ 1]'$

Along these lines, given a picture I, we acquire the x and y subordinates utilizing a convolution task:

$I_x = I * D_x$ And $I_y = I * D_y$

At that point the magnitude of the gradient is given by:

$|G| = (I_x^2 + I_y^2)^{0.5}$

what's more, orientation of the gradient is given by:

$\theta = tan^{-1}(I_y/I_x)$

Block Histogram and Feature Vector Generation

After angle calculation, the subsequent stage is to make the histogram of the cells. Inside the cell, every pixel makes a weighted choice for an introduction put together histogram channel based with respect to the qualities found in the calculation of the angles. The cells are rectangular, and the histogram channels are consistently spread more than 0 to 180 degrees, and the inclination is "unsigned". Concerning the vote weight, pixel commitment can be simply the slope greatness, or the square root or square of the inclination size.
The inclination qualities should be standardized locally so as to represent changes interestingly and light, which fundamentally includes consolidating/gathering the phones together into bigger, spatially-associated squares, which is the subsequent stage.
The HOG descriptor or highlight is then the vector of the segments of the standardized cell histograms from all the square areas.

K-NN (K- NEAREST NEIGHBOURS)

KNN can be utilized for both characterization and relapse prescient issues. Nonetheless, it is all the more generally utilized in arrangement issues in the business.
In KNN first load the data then Initialize the k value to get the predicted class, after class is identified iterate from 1 to total number of training data points then calculate the distance between test data and training data of each row. Here we will use Euclidean distance as our distance metric since it's the most popular method. Then sort the calculated distances in ascending order based on distance values. Then get top k rows from the sorted array. Then get the most frequent class of these rows. At last return the predicted class.

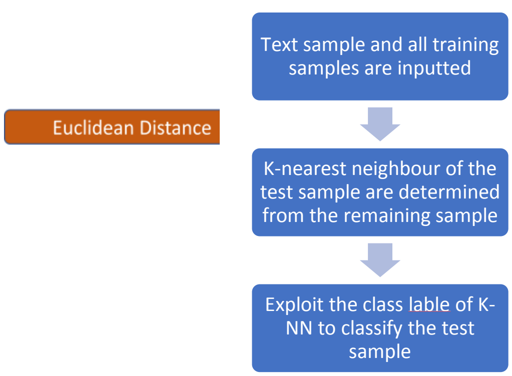

Figure 5. Working of K-NN algorithm

To assess any procedure we for the most part take a gander at 3 vital perspectives the same is showed in figure 5:
1. Simplicity to translate yield
2. Computation time
3. Prescient Power
Give us a chance to take a couple of guides to put KNN in the scale :

Table 1. The classification results on different methods

	Logistic Regression	CART	Random Forest	KNN
1.Easy to interpret output	2	3	1	3
2. Calculation Time	3	2	1	3
3. Predictive Power	2	2	3	2

KNN calculation fairs over all parameters of contemplations. It is generally utilized for its simple of elucidation and low count time.

IV. RESULTS AND DISCUSSIO

Scale and orientation analysis of LBP and HOG
Here we used two algorithms to illustrate why the proposed scheme is effective under scale variation. Brodatz is an image database containing 112 kinds of materials and each material was captured by different scales and orientation.

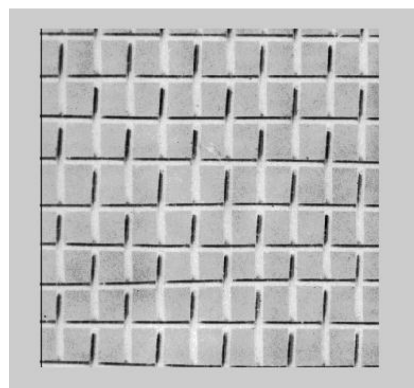

Figure 6. Trained image 1_1D1

Here we are considering two sub images(1_1D1 & 1_2D1) of the same class(D1) is shown in figure. 6 and figure 9 below, then for their corresponding Histogram bar chart is shown for both LBP and HOG algorithms.

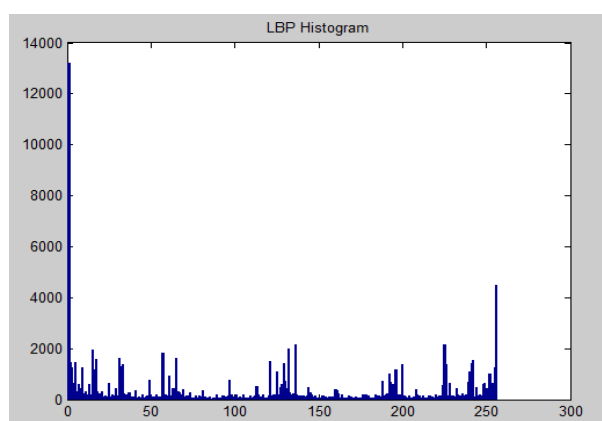

Figure 7. LBP Histogram for image 1_1D1

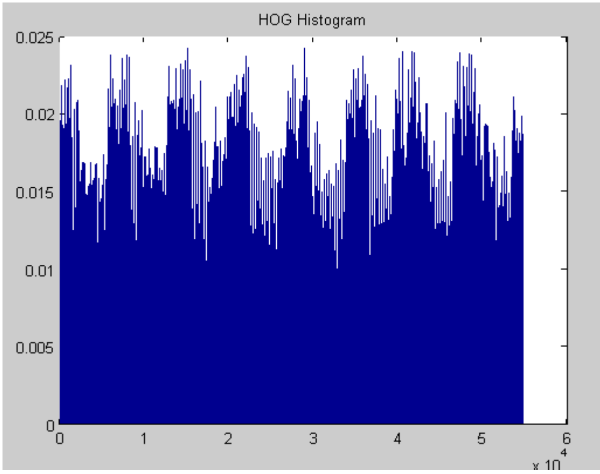

Figure 8. HOG Histogram for image 1_1D1

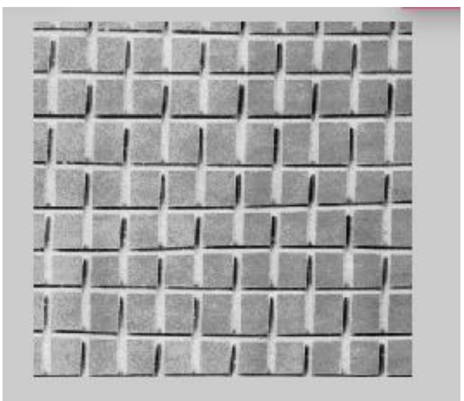

Figure 9. Trained image 1_2D2

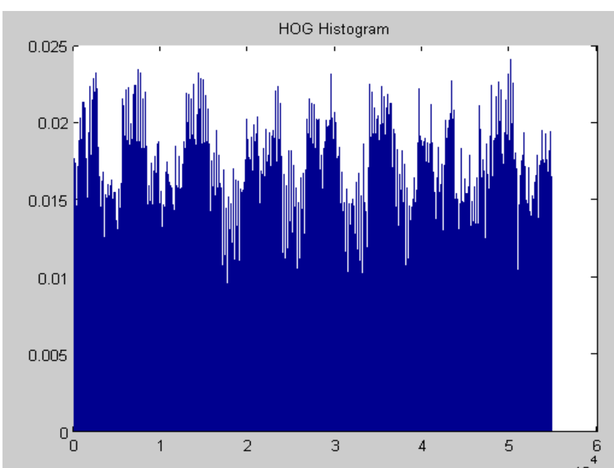

Figure 10. HOG Histogram for image 1_2D2

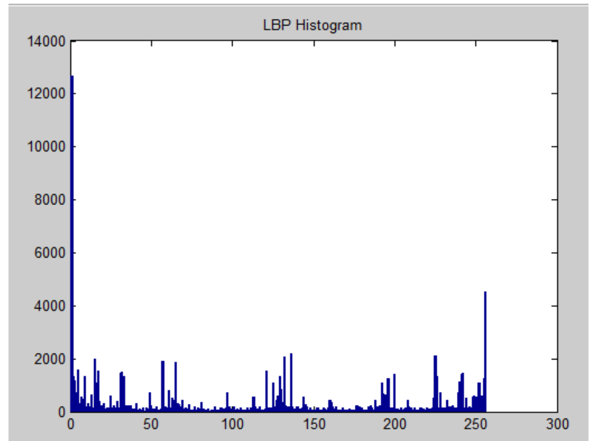

Figure 11. LBP Histogram for image 1_2D2

From the above bar chars I can say that for the same class of sub images the graph shows only slight variations in the orientation or feature extraction. If I take the difference between LBP algorithm feature extraction the distance is only 0.3 and HOG algorithm feature extraction the distance is only 0.02, so it is clear from the above charts that our algorithm extracting features of the images accurately.

Accuracy Comparison with Other Methods

In this subsection, we contrast our proposed highlight extraction technique and other five condition of-craftsmanship strategies for classification on the test datasets

(a) Method of [2] (meant by DTRCWT+DTCWT) The information texture picture is decayed by DTCWT and dual tree pivoted complex wavelet channel mutually, and texture component is gotten by joining the vitality and standard deviation of the unpredictable coefficients on each sub images.

(b) Method of [4] (meant by GGD+GVMD) The information texture picture is disintegrated by wavelet outlines with Mallat channels, the extents and periods of wavelet detail coefficients are demonstrated by summed up Gamma appropriation and summed up von Mises circulation individually. Parameters of the measurable models, got by means of test scale-free shape (SISE) estimation and most extreme probability (ML) estimation, are taken as texture component.

(c) Method of [6] (indicated by CLBP) Given an info texture picture, the neighborhood distinction sign-greatness change is connected to get its relating sign and size segments. Moreover, the middle dark dimension of the first picture is likewise determined. At that point three administrators, i.e., CLBP_S, CLBP_M and CLBP_C are utilized to code and develop the last element.

(d) Method of [19] (signified by PLBP) Given an information texture picture, the pyramid change is utilized to acquire consecutive pictures with various goals, and the blend of those LBP descriptors at all pyramid space is used as textural include.

(e) Method of [18] LBPDTCWT+LPDTCWTE(EW) denotes the method combining two descriptors with equal weights, and LBPDTCWT+LPDTCWTE(OW) denotes the method combining our proposed two descriptors with the optimal weights. One can find that LBPDTCWT, LBPDTCWT + LPDTCWTE(EW), LBPDTCWT+ LPDTCWTE(OW) and PLBP provide perfect classification.

Table 2 *The classification results on Brodatz for different methods*

Feature	Training image per number of classes (n)								
	1	2	3	4	5	6	7	8	Avg.
DTRCWT+DTCWT	86.27	92.96	94.56	94.58	95.79	96.83	97.29	97.35	94.45
GGD+GVMD	86.83	93.79	94.78	96.62	97.66	98.91	99.05	99.22	95.86
CLBP	93.61	95.83	96.47	97.22	97.68	97.91	98.1	98.43	96.91
PLBP	94.88	98.02	99.07	99.33	99.48	99.95	100	100	98.84
LBPDTCWT+ LPDTCWTE(EW)	98.33	99.7	100	100	100	100	100	100	99.75
LBPDTCWT+ LPDTCWTE(OW)	98.33	100	100	100	100	100	100	100	99.79
LBP-HOG	98.91	100	100	100	100	100	100	100	99.86

In order to remove global intensity and contrast, all images in dataset Brodatz are normalized before feature extraction, which makes their corresponding histograms follow a fairly uniform distribution. DTRCWT+DTCWT, LPDTCWTE achieve slightly lower performance since their energy based features are very sensitive to histogram equalization. In the Proposed method i.e, LBP-HOG with KNN classifier achieves 99.86% more than the LBPDTCWT+ LPDTCWTE(OW), so it is accurate than other algorithms. And additionally we calculated specificity and sensitivity and specificity also 100% achieved.

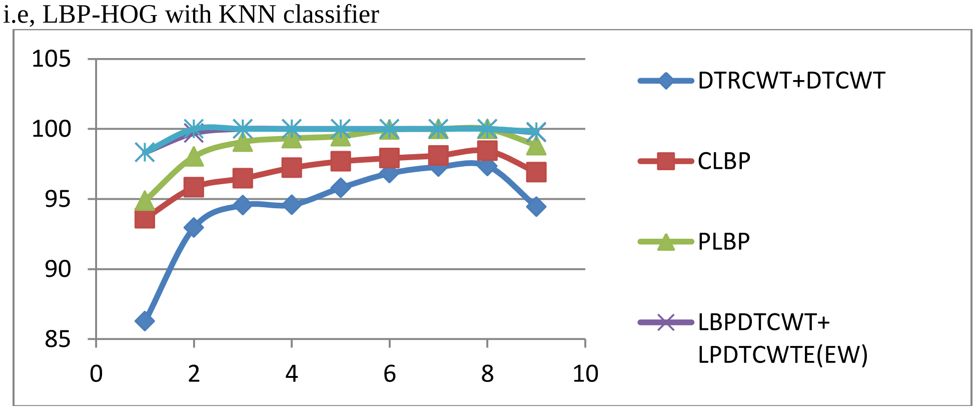

Figure 12. *The classification results on Brodatz for different methods*

V. CONCLUSION AND FUTURE SCOPE

The trials directed on BRODATZ dataset utilizing LPB-HOG and profound system's highlights demonstrate that LPB include extractor has outflanked different techniques, particularly while utilizing K-NN calculation as a classifier.
Nonetheless, the outcomes acquired by HOG highlight extractor were not tasteful as the model has failed to meet expectations by the parameters utilized in the present investigation. Be that as it may, these parameter decisions were made to remain steady as far as highlight's measurements over the different component extractor models. In the future research, it might plan to focus on the promising discoveries displayed in these calculations and keep on dealing with issues identified with the utilized techniques. Using same calculations can be utilized to perceive moving articles. This may deal with moving items discovery.

REFERENCES

[1] S.C. Kim, T.J. Kang. *Texture classification and segmentation using wavelet packet frame and Gaussian mixture model*. Pattern Recognition, 2007, 40(4): 1207-1221.

[2] M. Kokare, P.K. Biswas, B.N. Chatterji. *Texture image retrieval using new rotated complex wavelet filters*. IEEE Transactions on Systems, Man, and Cybernetics, 2005,35(6):1168–1178.

[3] K. Jafari-Khouzani, H. Soltanian-Zadeh. *Rotation-invariant multiresolution texture analysis using Radon and wavelet transforms*. IEEE Transactions on Image Processing, 2005, 14(6):783-795.

[4] E.D. Ves, D. Acevedo, A. Ruedin, X. Benavent. *A statistical model for magnitudes and angles of wavelet frame coefficients and its application to texture retrieval. Pattern Recognition*, 2014,47(9): 2925–2939.

[5] M. Heikkila, M. Pietikainen, C. Schmid. *Description of interest regions with local binary patterns. Pattern Recognition*, 2009,42(3): 425–436.

[6] Z. Guo, L. Zhang L, D. Zhang. *A completed modeling of local binary pattern operator for texture classification*. IEEE Transactions on Image Processing, 2010,19(6):1657–1663.

[7] Y. He, N. Sang, C. Gao. *Pyramid-Based Multi-structure Local Binary Pattern for Texture Classification. Formal Pattern Analysis & Applications*, 2010, 6494:133-144.

[8] X. Qian, X.S. Hua, P. Chen, L. Ke. PLBP: *An effective local binary patterns texture descriptor with pyramid representation*. Pattern Recognition, 2011,44(10-11): 2502–2515.

[9] B. Ameur, S. Masmoudi, A.G. Derbel, A.B. Hamida. *Fusing Gabor and LBP feature sets for KNN and SRC-based face recognition*. in: Proceedings of the ATSIP, 2016, 453-458.

[10] Shuai ZHOU and Yanhong LIU, Member, IEEE and Keqiang LI. *Recognition of Multi-scale Multi-angle Gestures Based on HOG-LBP Feature*, 2018 IEEE 978-1-5386-9582-1/18

[11] Kennedy Chengeta, Serestina Viriri School of Maths, Statistics & Computer Science, *A Survey on Facial Recognition based on Local Directional and Local Binary Patterns*,2018 978-1-5386-1001-5/18

[12] Taha J. Alhindi, Shivam Kalra, Ka Hin Ng, Anika Afrin, Hamid R. Tizhoosh, *Comparing LBP, HOG and Deep Features for Classification of Histopathology Images*, 8-3 July, 2018

[13] S. P. Priyal, P. K. Bora, *A robust static hand gesture recognition system using geometry based normalizations and Krawtchouk moments*, Pattern Recognition, vol. 46, no. 8, pp.2202-2219, 2013.

[14] J. Žemgulys, V. Raudonis, and R. Maskeliūnas *Recognition of basketball referee signals from videos using histogram of oriented gradients (HOG) and support vector machine (SVM)*, Procedia Computer Science, vol. 130, pp.953-960, 2018.

[15] J. Konecny, M. Hagara, *One-shot-learning gesture recognition using HOG-HOF features*, Journal of Machine Leaning Research, vol. 15, pp. 2513-2532, 2014.

[16] Y. Zhou, G. Jiang, and Y. Lin, *A novel finger and hand pose estimation technique for real-time hand gesture recognition*, Pattern Recognition, vol. 49, pp.102-114, 2015.

[17] Ding, Y., H. Pang, and X. Wu. *Static hand-gesture recognition using HOG and improved LBP features*, International Journal of Digital Content Technology & Its Application, vol. 5, no.11, pp.236-243, 2011.

[18] Peng Yang, Fanlong Zhang and Guowei Yang. *Fusing DTCWT and LBP based Features for Rotation, Illumination and Scale Invariant Texture Classification*, IEEE Access journal 2169-3536 2018

[19] X. Qian, X.S. Hua, P. Chen, L. Ke. PLBP: An effective local binary patterns texture descriptor with pyramid representation. Pattern Recognition, 2011,44(10-11): 2502–2515.

Authors Profile

Mrs. Sunanda pursed Bachelor of Engg. from VTU University in year 2012. and currently pursuing M.tech in Department of Computer Science and Engineering, VTU University since 2018.

Mr.Arun Biradar is woring as a professor and Head in Department of computer science Engg., East West Institute of Technology. He has published more than 50 research papers in national and international coferences and journals. His research areas are Wireless Ad-Hoc networks, Computer Networks, Software Engg. Genetic Algorithms and Machine Learning.