World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(Research Article)

Check for updates

A novel texture descriptor Octagonal-based Directional Distance Local Binary Pattern (ODLBP) for image classification

Md Anwarul Islam [1,*], Sajal Mondal [2] and Farjana Akter [2]

[1] *Department of Computer Science and Engineering, Sheikh Hasina University, Netrokona, Bangladesh.*
[2] *Department of Computer Science and Engineering, Green University of Bangladesh, Dhaka, Bangladesh.*

World Journal of Advanced Research and Reviews, 2024, 24(03), 026–036

Publication history: Received on 20 October 2024; revised on 30 November 2024; accepted on 02 December 2024

Article DOI: https://doi.org/10.30574/wjarr.2024.24.3.3674

Abstract

Various statistical descriptors are available for extracing features from texture images, with the Local Binary Pattern being among the most widely used methods for uncovering the fundamental structure of a texture. Each variants have their own advantages; however, these algorithms provide some major issues that needs to address. In order to solve these issues, we introduce a novel texture descriptor known as the octagonal directional distance local binary pattern (ODLBP) for image classification. The descriptors explain new approaches to feature extraction, while the computational framework is very different and much superior to prior methods. This is a unique descriptor that makes a binary calculation with a thorough comparison of the central pixel and its adjacent and secondary neighboring pixels, thus offering substantial improvement over the conventional techniques. Thus, ODLBP is highly recommended for improving the texture representation, as no pixel value is overlooked. This approach is thorough enough to allow for more complete and accurate feature extraction, providing more pronounced image representations compared to those obtained through previous methods. The efficiency of ODLBP descriptors has been checked quite thoroughly against popular datasets like KTH-TIPS, KTH- TIPS 2b, Caltech101, CUReT, Leeds Butterfly and Brodatz. The results have proved that ODLBP is very easy to realize and implement; on the other hand, it ensures superior performance in image classification.

Keywords: Octagonal Directional Distance Local Binary Pattern (ODLBP); Local Binary Pattern (LBP); Local Ternary Pattern (LTP); Feature Extraction; and Texture classification

1. Introduction

The characterization of different regions in an image based on their texture is referred to as texture analysis. This technique aims to quantify descriptive terms such as rough, smooth, silky, or bumpy by evaluating the spatial variations in pixel intensities. Variations in intensity levels, or gray levels, determine the roughness or bumpiness of the texture. Texture analysis plays a crucial role in various image processing and computer vision applications, including object detection, detection of flaws on the surface, identification of patterns, analysis of medical images, document analysis, face detection, fingerprint, detection and classification, and many more. In image processing, feature extraction is the most important matter, and this is also a big challenge. Feature extraction involves extracting significant and pertinent details (features) from unprocessed data (e.g. pictures) to represent it more effectively and concisely. In the context of image processing, feature extraction involves analyzing the image to identify and extract important features such as edges, corners, textures, colors, shapes, etc. These features can then be used as input for various machine learning algorithms, such as image classification [1], [2], [3], [4], recognition [5], [6], and segmentation. We are already aware that this application area has been implemented in significant locations, but it poses a significant obstacle to achieving an accurate and flawless image structure. However, with a robust algorithm in place, the technology in image processing will experience rapid and exponential growth. Already previously

* Corresponding author: Md Anwarul Islam

many kinds of descriptors are huge work in this sector. Here, the successful exploitation of texture analysis can be seen in these examples. In the last few decades, several techniques for extracting textural features have been introduced; however, Local Binary Pattern (LBP) [7] is currently the most widely utilized technique. The LBP is the simplest approach for texture description which was presented by Ojala et al. LBP [7] works with all the pixels and compares each pixel with its neighbors, which surround each pixel in a circle. A binary pattern that represents these relationships is then transformed into a histogram. In fact, the success of LBP [7] has stimulated a large amount of research into extensions that address various problems and requirements. Numerous types of research, including Local Ternary pattern (LTP) [8] which was proposed by Tan and Triggs (2010) for face recognition. Local Directional Pattern (LDP) [9] was proposed by Jabid et al., 2010a, Local Directional Ternary Pattern (LDTP) [10] was proposed by Chahi at all., Zhang et al. proposed Local Derivative Pattern (LDP) [11], Local Tetra Pattern (LTrP) [12] was proposed by Murala, Adjacent evaluation of local binary pattern (AELBP) [13] was proposed by song adjacent. A new descriptor octagonal-based directional distance local binary pattern is proposed for texture classification. This new encoding system is more useful for understanding the texture of images than others. This research provides an impartial, systematic, and comprehensive evaluation of the proposed descriptor in comparison to numerous recent state-of-the-art techniques in the field of texture classification. This article's remaining sections are organized as follows: The proposed ODLBP is detailed and presented in section 2. In section 3 Experimental analysis is described in detail. Section

2. Material and methods

Texture segmentation is a critical process in image analysis that involves the automated delineation of boundaries between distinct textured regions within an image. This process is of paramount importance in various domains of image pro-cessing. For instance, in agriculture, texture segmentation is employed to analyze crop images for the classification of pests, diseases, and weeds. In forensic science, it is instrumental in enhancing and examining images such as fingerprints and DNA samples. In the field of medical imaging, it contributes to improving the quality of diagnostic images, such as X- rays and CT scans, by facilitating the clear visualization of different anatomical structures. Additionally, in industrial automation, texture segmentation is utilized to inspect products and components on assembly lines, detecting defects and ensuring stringent quality control. The literature on texture analysis presents a wide array of feature descriptors that have been developed and employed over the years. Most of these descriptors focus on the spatial relationships between pixels within a localized neighborhood in gray scale images. Among the many techniques proposed for characterizing textured images, traditional methods include nearest neighbor information-based approaches [7] [8] [9] [10], co-occurrence matrix-based approaches [14], and filter- based methods such as Gabor filters [15] and wavelets [16].

2.1. Local Binary Pattern (LBP)

Ojala et al. proposed the Local Binary Pattern (LBP) [7] as a means of texture classification. To implement the Local Binary Pattern technique, a binary pattern is computed for each pixel in an image by comparing the pixel's value to its neighboring pixels within a 3x3 square neighborhood. The LBP [7] value is then calculated based on two equations illustrated in figure 1. Unlike earlier approaches to texture classification that used single values to measure texture, LBP [7] suggests using the distribution of feature values. This makes it a more effective texture descriptor. However, it has a limitation in that it can only encode relative values of the gradient magnitude and cannot change its own position.

$$LBP = \sum_{p=0}^{7} 2^p \xi \left(I_p - I_c \right) \qquad (1)$$

$$\xi(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{else} \end{cases} \qquad (2)$$

2.2. Local Directional Pattern (LDP)

Jabid et al. (2010a, 2010b) proposed a novel approach for extracting significant features from texture images, which they called Local Directional Pattern (LDP) [11]. Rather than focusing on intensity, it captures directional information from central pixel of a gray scale image patch measuring 3×3 the surrounding area by assigning an 8-bit binary code to the pixels. The binary code is derived by applying Kirsch masks in eight different directions ($M_0 - M_7$) to the local 3×3 gray scale image patch and comparing with the maximum prominent value and creating a 1,0 binary pattern. After that adding Gaussian White noise on the binary pattern. Given below are the corresponding Eq 3 which is used for calculating the directional information in the neighborhood of the Local Directional Pattern.

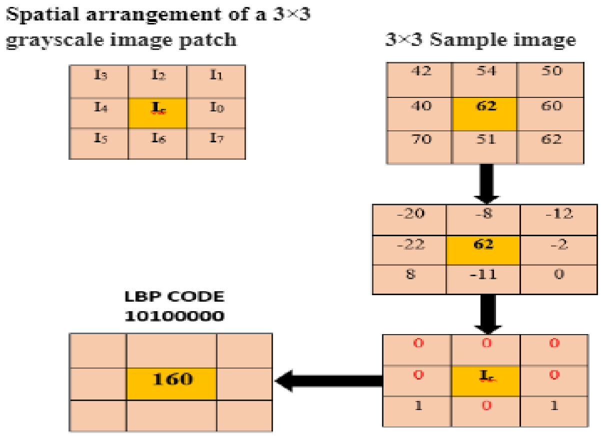

Figure 1 Threshold and Encoding Process as basic in Local Binary Pattern LBP

$$LDP = \sum_{p=0}^{7} 2^{p}\xi\left(|ER_p| - |ER_k|\right) \qquad (3)$$

Where ER_k is the k-th most significant directional response. We noticed that The LDP feature works by ranking the most notable responses in various directions to encode the texture of an image. Even in the presence of noise, the LDP feature is less likely to have the positions of the more significant edge responses altered, which makes it a more reliable feature descriptor. But it also has limitations, it uses complexity on the Kirsch mask and all directions are treated equally. LDP [11] codes are created just based on the value of edge reactions in eight directions/neighborhoods and it ignores the center pixel. Although the center pixel is vital in numerous applications.

2.3. Local Ternary Pattern (LTP)

Local ternary pattern [8] is another texture descriptor that by Tan and Triggs (2010) extended basic LBP [7] to three three values encoded. The three extended values are (-1,0,1) ternary codes by using a threshold Δ, where the threshold Δ value is specified by the user. The three values function are shown in Eqs 4. By corresponding, the three-valued function LTP [8] has been split into two sections. Local ternary pattern upper (LTP_U) and Local ternary pattern lower (LTP_L) which is shown in Eq 5 and Eq 6. The number of possible patterns generated by the LTP [8] is illustrated through a grayscale image patch of size 3 × 3, which can result in $2 * 2^8$ different patterns.

$$\varphi(I_p, I_c, \Delta) = \begin{cases} +1 & I_p >= I_c + \Delta, \\ 0 & |I_p - I_c| < \Delta, \\ -1 & I_p <= I_c - \Delta, \end{cases} \qquad (4)$$

$$LTP_U = \sum_{p=0}^{7} 2^{p}\xi\left(I_p - I_c - \Delta\right) \qquad (5)$$

$$LTP_L = \sum_{p=0}^{7} 2^{p}\xi\left(I_c - I_p - \Delta\right) \qquad (6)$$

LTP [8] is not strictly invariant to gray scale changes and here it is difficult to find the suitable threshold value also it is noise sensitive which are limitation of this descriptor.

2.4. Local Directional Ternary Pattern (LDTP)

Chahi et al. The descriptor suggested is known as the Local Directional Ternary Pattern. (LDTP) [10], in-consolidate there are two types of compass masks. One is 2nd derivative Gaussian mask which works to avoid noise fervency and make the method robust to illumination changes. Another is Frei- Chen which increases the encoded structure information. After using these LDTP [10] solve most of the previous approaches problem well and produce the better those approaches. But the Frei Chen Mask time complexity is high because Frei-Chen masks use root operation and take much more time to calculate than real-time. Given below are the Eq 7 and Eq 8 that are used for calculating the descriptor.

$$\mu = \frac{1}{9}\left(I_c + \sum_{p=0}^{7} I_p\right) \qquad (7)$$

$$\vartheta(x,y) = \begin{cases} +1 & \text{if x>=0 and y>=0,} \\ -1 & \text{if x<=0 and y<=0,} \\ 0 & else \end{cases} \qquad (8)$$

2.5. Local Tetra Pattern (LTrP)

Subrahmanyam Murala et al. [12] deals with the Local Tetra Pattern proposal of second orders, which will be calculated in vertical and horizontal directions. When the values of I_0 degrees and 90 degrees are equal to or greater than 0, the direction will be 1. Again, when the value of I_0 is less than 0 and the value of $I_9$0 degree is equal to or greater than 0 then the direction will be 2. When the value of I_0 degree and $I_9$0 than or equal to 0 and if the value of $I_9$0 degrees is less than degree is from 0 then the direction will be 3. If I_0 is greater 0 then the direction will be 4. So let's say that the possible direction of each center pixel can be 1,2,3,4. The image will be converted to 4 value directions. After that, we get an 8- bit tetra pattern for each center pixel. And each direction is converted to 3 binary patterns. After identifying local patterns, the entire image is represented in a histogram. AELBP [13] tries to solve the noise sensitivity of the LBP [7] descriptor. In the LBP [7] descriptor, a new bit matrix was created comparing the neighbor pixels with the center pixel. But we find that the noise cannot be completely removed by LBP [7]. For which a new descriptor AELBP [13] is proposed by extending LBP [7]. In LBP [7] neighbor pixel values can be changed by random noise at any time for that reason AELBP [13] creating evaluation windows around the neighbor to solve this problem. AELBP [13] descriptor first defines the adjacent evaluation window and its center is called G_c and its neighbor pixels are called the center pixel of the evaluation window. The center pixel of the evaluation window is denoted by a_p. After excluding the value of the center pixel of the evaluation window and averaging the neighboring pixels, we get the value of the center pixel, thus after extracting the value of all the evaluation windows app. Replace the values of adjacent evaluation windows with the value of evaluation window app, then LBP [7] descriptor has been used compared with the center value G_c.

$$AELBP_{P,R} = \sum_{P=0}^{P-1} \varphi(a_p - g_c)2^P, \qquad (9)$$

$$\varphi(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \qquad (10)$$

3. Results and discussion

3.1. Octagonal-Based Directional Distance Local Binary Pattern (ODLBP)

Local Binary Patterns (LBP) is a simple yet widely utilized technique for describing texture features. It was first introduced by Ojala et al. [7] as a basic operator to characterize local patterns, achieving notable success in texture image classification [17]. While LBP was originally developed for texture classification [18], [19], it has been applied in various fields, including shape localization [20], face recognition [8], [11], texture recognition [21], [22], and medical image analysis [23], [24]. LBP serves as a local descriptor, but it is sensitive to noise and rotation, generating an extensive number of features. To mitigate these issues, Ojala et al. proposed robust and rotation-invariant versions of LBP [25], [26]. Since its introduction, several LBP extensions have been developed to provide more discriminative features for texture analysis. These variants enable the extraction of a greater number of features, with feature counts increasing exponentially as the neighborhood size grows [27], [28]. For example, Ojala et al. combined LBP with a variance operator in the LBP/VAR method [29], enhancing its ability to extract distinctive features. Another variant, the Local Ternary Pattern (LTP), quantize intensity differences into three levels [8], while derivative-based LBP uses gradient patterns to improve feature extraction [20]. Other notable advancements include Dominant LBP (DLBP), proposed by Liao et al. [30], which identifies the most frequently occurring patterns and includes both uniform and non-uniform patterns for capturing textural details. Centrosymmetric LBP was developed to reduce the number of features generated by traditional LBP [31]. Additionally, Local Derivative Patterns (LDP) utilize higher-order differences to capture more detailed features, although they are more prone to noise [11]. Despite its extensive use and advancements in texture classification and pattern recognition, further exploration is needed to refine the fundamental principles of LBP and its derivatives. In this paper, we proposed a new variant of texture feature descriptor. The proposed octagonal-based directional distance local binary pattern (ODLBP) is a novel feature extraction technique designed to enhance the effectiveness and accuracy of traditional methods. This technique is an advancement over the local directional ternary pattern (LDTP) [10] introduced by Chahi et al. in 2018, which primarily focuses on the center pixel and its immediate neighbors using two types of compass masks. These masks, while effective, present a significant complexity in their application. In contrast, ODLBP extends this concept by not only considering the center pixel and its immediate neighbors but also incorporating the neighbors of these neighbors. This multilevel neighborhood approach captures a broader contextual relationship, considering directional orientations such as horizontal, vertical, and diagonal alignments. The methodology of ODLBP involves a detailed comparative analysis between the center pixel and its surrounding pixels in various directions. Specifically, the immediate neighbor pixel values are compared with the center value across horizontal, vertical, and diagonal axes. This comparison generates a 3×3 matrix of values, which are subsequently binarized using the Local Binary Pattern (LBP) method. The LBP method transforms the matrix values into binary form, as it operates on a dichotomous (0 or 1) system, facilitating the conversion of these values into a singular ODLBP pattern value for the center pixel.

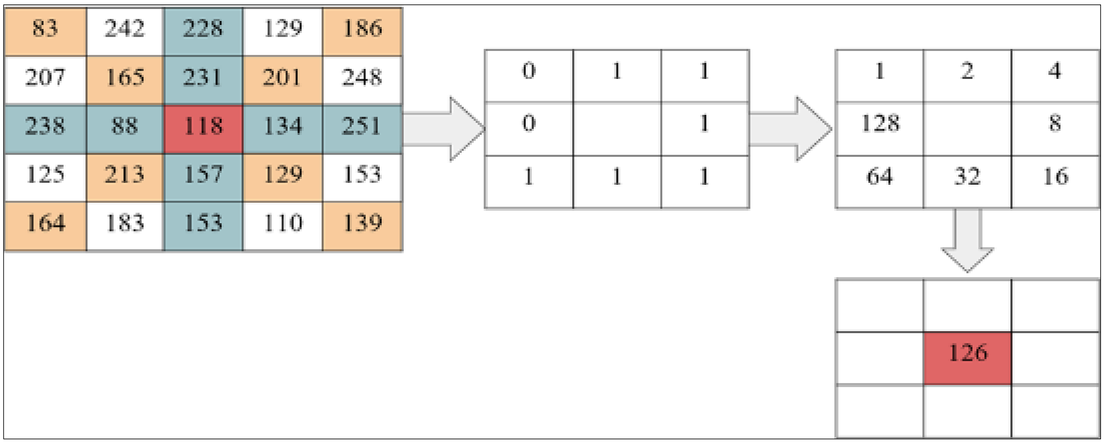

Figure 2 The encoding process of ODLBP

3.1.1. Working Procedure

This comprehensive approach allows for the construction of a feature map, where each pixel's pattern is individually assessed and transformed. The feature map effectively encapsulates the intricate textural details of the image, serving as the foundation for the final feature vector. The encoding process is illustrated in Fig. 2. To generate the feature vector, a 5 × 5 matrix is utilized, where the center value is updated after each operation. The algorithm incorporates three key values: the center pixel value I_c, the neighboring pixel value I_{px}), and the value of the second neighbor pixel I_{py}. In LDTP [10], they used frei-chen mask to calculate directional pattern, however, there is no specific pattern. Besides, they did not mention why the value of mask changes for different direction. Moreover, they use the same matrix for 8 direction mask which is redundant. In order to solve this issue, we employ the concept of second neighbor. The second neighbor value is chosen from the same direction as the neighbor selected from the center. Thus, this algorithm provide more directional information than LDTP. The first gradient value, representing the difference between the center pixel and its immediate neighbor, is computed using Eq. 11. Similarly, the second gradient value is derived from the center pixel and the second neighbor using Eq. 12. These gradient values capture shape-related information, which enhances performance. Subsequently, texture information is calculated using Eq. 14, where the parameters τ and ω are applied as defined in Eq. 13. If τ and ω belong to the same cluster, the information is updated to 1; otherwise, it remains 0. This leads to clearer and more distinct edge detection. Thus, this algorithm keeps two prominent feature information, gradient as well as texture.

$$\tau = I_c - I_{px} \qquad (11)$$

$$\omega = I_c - I_{py} \qquad (12)$$

The histogram of the feature map, which represents the distribution of various patterns across the image, forms the ultimate feature vector. This feature vector is instrumental in various image analysis tasks, offering enhanced discrimination capabilities and robustness.

$$\theta(x, y) = \begin{cases} 1 & if \quad x > 0 \ and \ y > 0 \\ 0 & else \end{cases} \qquad (13)$$

$$ODLBP = \omega(\tau, \omega) \qquad (14)$$

Here Ic is the center pixel which is 118 in the figure. Ipx is the neighboring pixel for example 88 (left side value of the center pixel) and Ipy is the second neighbor (neighbor of neighbor) such as 238. The value is calculated for every neighboring pixel using Eq. 13. Calculative neighboring pixels are colored as same color. In this context, the newly designated center pixel value, denoted as Ic, is established at 126. This value serves as a pivotal reference point for subsequent comparisons and calculations. The immediate neighboring pixel values are represented as Ipx , while the secondary level of neighboring pixels, or the neighbors of the neighbors, are denoted as Ipy . The algorithm proceeds by meticulously comparing these values, Ipx and Ipy against the central pixel value Ic . This comparative analysis spans multiple orientations, including horizontal, vertical, and diagonal alignments, ensuring a comprehensive capture of the textural nuances present in the image. The resulting feature vector, articulated through Equation 13, serves as a robust and discriminative descriptor of the image's textural characteristics.

3.2. Data Set

KTH-TIP: The KTH-TIPS [32] (Textures under Varying Illumination, Pose, and Scale) dataset is a significant resource in the field of computer vision, particularly for texture recognition and classification tasks, as delineated by Fritz et al. Developed by the KTH Royal Institute of Technology in Sweden, this dataset is designed to test the robustness of algorithms under varying conditions, making it an essential tool for researchers focused on texture analysis. The KTH-TIPS dataset consists of images from 10 different texture categories, such as Aluminum Foil, Brown Bread, Corduroy, Cotton, Cracker, Linen, Orange Peel, Sandpaper, Sponge, Styrofoam.

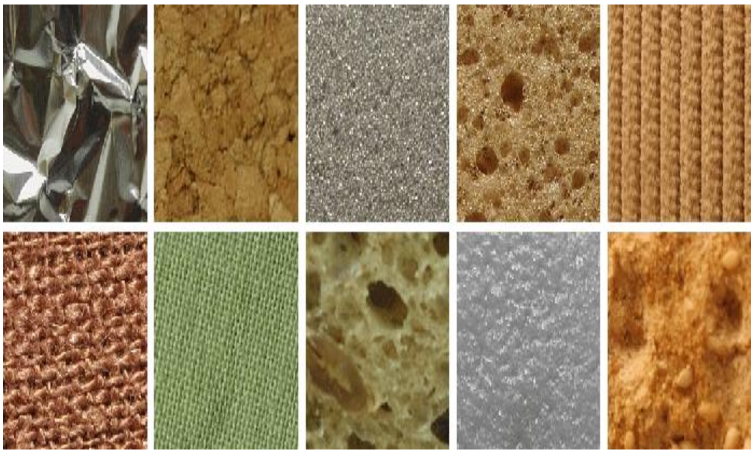

Figure 3 KTH-TIPS Dataset

KTH-TIP2b: The KTH-TIP2b [33] the KTH-TIPS2b dataset is an extended version of the KTH-TIPS dataset, designed for more advanced texture recognition and classification tasks in computer vision. It includes images of 11 texture categories, each captured under varying conditions of illumination, pose, and scale, as well as at different times to

Figure 4 KTH-TIPS 2B Dataset

introduce aging effects. The textures are photographed at three different scales and from several viewpoints, making the dataset particularly challenging and valuable for testing the robustness and generalization capabilities of texture recognition algorithms. This dataset is often used to evaluate models' ability to recognize textures under real-world variations. Caltech 101: The Caltech 101 [34] dataset is a widely used collection of images designed for object recognition and image classification tasks in computer vision. It includes images from 101 distinct object categories, such as helicopter, elephant, and chair, along with a background category for images that don't belong to these classes. Each category typically contains around 40 to 800 images, with most categories having about 50 images. The images have a resolution of approximately 300x200 pixels. This dataset has been instrumental in advancing research in computer vision by providing a diverse and challenging benchmark for evaluating the performance of machine learning models.

Figure 5 Caltech 101 Dataset

CUReT: An extensive and popular dataset in computer vision, the CUReT [35] (Columbia-Utrecht Reflectance and Texture) dataset is used to explore material appearance, surface reflectance, and texture recognition. The CUReT [35] dataset, created by scientists at Utrecht and Columbia Universities, is a vital tool for researchers studying surface reflectance modeling and texture analysis because it captures the intricate relationships between lighting, viewing angles, and material characteristics. It includes images of 61 different texture categories such as, Sandpaper, Brick, Limestone, Leather, Wool, Rough Metal, Aluminum, Foil, Plastic, Concrete, Fabric. Each of the 61 texture categories is represented by hundreds of images, with variations in viewing angles and illumination directions. The total number of images in the CUReT [35] dataset is approximately 92,000, providing a rich set of data for training and evaluating texture recognition models.

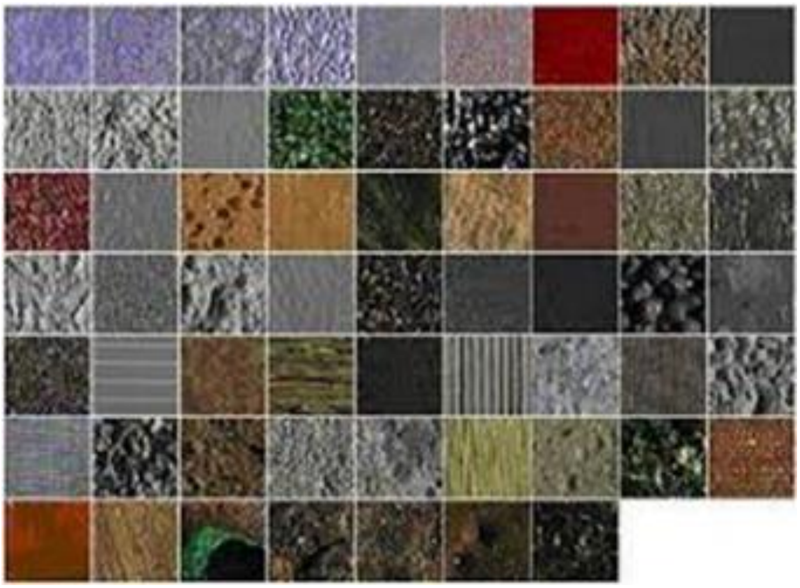

Figure 6 CUReT Dataset

Brodatz: One of the most well-known and often used texture datasets in computer vision, especially for applications involving texture analysis and classification, is the Brodatz dataset [36]. This dataset, named for the photographer and artist Phil Brodatz, who released the original texture photographs in his 1966 book" Textures: A Photographic Album for Artists and Designers," has proven to be invaluable in the testing and development of texture recognition algorithms. The Brodatz [36] dataset consists of 112 grayscale texture images, each representing a different texture type such as, Fabric, Wood, Stone, Leather, Sand, Paper. The images in the Brodatz dataset [36] are typically 640x640 pixels or larger, providing ample detail for texture analysis.

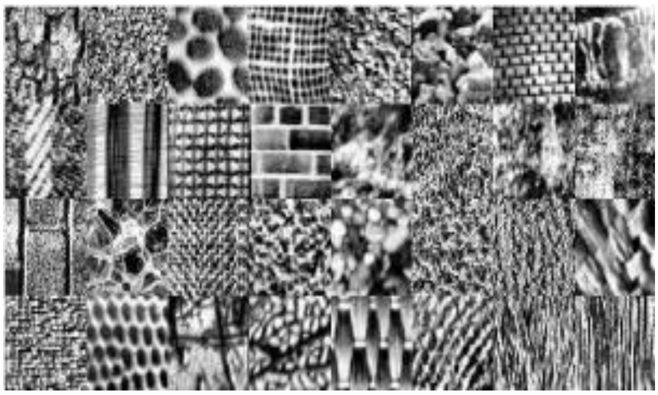

Figure 7 Brodatz Dataset

3.3. Experimental Analysis

In order to train and find out the accuracy we use spark random forest algorithm. Since spark is a distributed computing system and provide faster and scalable library for machine learning. Here data is splatted 80% train and 20% test data. To evaluate the excellence of our proposed algorithms, we employed several distinctive datasets, including KTH-TIPS [32], KTH-TIP2b [33], Caltech101 [34], CUReT [35], and the Brodatz dataset [36]. Our proposed algorithm, Octagonal Based Directional Distance Local Binary Pattern (ODLBP), demonstrates superior performance compared to existing algorithms across all these datasets. Since the proposed approach provides gradient information that preserves shape characteristics, the accuracy is improved. Furthermore, directional information is maintained by utilizing the second neighbor in the same direction relative to the center. Consequently, the outcome delivers more direction-specific information, addressing the challenge of applying directional masks for different directions and reducing the algorithm's complexity. Additionally, texture analysis is performed when both gradient values fall into the same cluster. For this reason, the proposed method performs deep edge detection for each pixel and outperforms existing algorithms in terms of accuracy. As demonstrated in Table I, our proposed method achieved the highest accuracy rates, with 91.36% for KTH-TIPS [32], 93.42% for KTH-TIP2b [33], 100% for Leeds Butterfly 92.89% for Caltech101 [34], 90.60% for CUReT [35], and 100% for the Brodatz dataset [36].

Table 1 Comparison Table

Dataset	**Existing**	**Method**			**Proposed Method**
	LBP	LTP	LDP	LDTP	ODLBP
KTH -TPS	85.3	88	87.5	89	91.36
KTH ˉTIPS S2B	61.5	80.12	70.4	80	93.42
Leeds Butterfly	56.93	66.32	70.52	75	100
Caltech-101	66.4	82.5	74.23	78	92.89
Curet	87	89.5	88	90.5	90.60
Brodatz	91	93.5	92	94.5	100

4. Conclusion

In this work, we introduce a novel feature extractor called the Octagonal-based Directional Distance Local Binary Pattern (ODLBP). This innovative method excels at reducing redundant pixel values in an image while preserving essential information. Unlike traditional techniques, the ODLBP method. combines distance and directional orientation to ensure that all critical pixel values are retained, leading to enhanced image processing accuracy. The ODLBP stands out due to its robustness and efficiency, offering a more refined approach compared to conventional methods. It improves the clarity and structural integrity of images, providing a more precise and resilient representation.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

Statement of informed consent

Informed consent was obtained from all individual participants included in the study.

References

[1] M. M. A. Misty, M. A. I. Abir, S. Mondal, M. Z. Islam, and M. M. Islam, "Noise-aware-based texture descriptor, evaluation adjacent distance local ternary pattern eadltp for image classification," in International Confer- ence on Big Data, IoT and Machine Learning. Springer, 2023, pp. 291–302.

[2] M. M. A. Misti, S. Mondal, M. A. I. Abir, and M. Z. Islam, "A novel tex- ture descriptor evaluation window based adjacent distance local binary pattern (eadlbp) for image classification," in International Conference on Machine Intelligence and Emerging Technologies. Springer, 2022, pp. 309–317.

[3] T. T. Vuong, B. Song, K. Kim, Y. M. Cho, and J. T. Kwak, "Multi-scale binary pattern encoding network for cancer classification in pathology images," IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 3, pp. 1152–1163, 2021.

[4] E. S. Gemeay, F. A. Alenizi, A. H. Mohammed, M. H. Shakoor, and R. Boostani, "Weighted constraint feature selection of local descriptor for texture image classification," IEEE Access, vol. 11, pp. 91 673–91 695, 2023.

[5] Z. Li, B. Li, S. G. Jahng, and C. Jung, “Improved vgg algorithm for visual prosthesis image recognition,” IEEE Access, 2024.

[6] Z. Liu, H. Wang, T. Zhou, Z. Shen, B. Kang, E. Shelhamer, and T. Darrell, “Exploring simple and transferable recognition-aware im- age processing,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 45, no. 3, pp. 3032–3046, 2022.

[7] T. Ojala, M. Pietika¨inen, and D. Harwood, “A comparative study of texture measures with classification based on featured distributions,” Pattern recognition, vol. 29, no. 1, pp. 51–59, 1996.

[8] X. Tan and B. Triggs, “Enhanced local texture feature sets for face recognition under difficult lighting conditions,” IEEE transactions on image processing, vol. 19, no. 6, pp. 1635–1650, 2010.

[9] T. Jabid, M. H. Kabir, and O. Chae, “Gender classification using local directional pattern (ldp),” in 2010 20th International conference on pattern recognition. IEEE, 2010, pp. 2162–2165.

[10] Chahi, Y. Ruichek, R. Touahni et al., “Local directional ternary pattern: A new texture descriptor for texture classification,” Computer vision and image understanding, vol. 169, pp. 14–27, 2018.

[11] B. Zhang, Y. Gao, S. Zhao, and J. Liu, “Local derivative pattern versus local binary pattern: face recognition with high-order local pattern descriptor,” IEEE transactions on image processing, vol. 19, no. 2, pp. 533–544, 2009.

[12] S. Murala, R. Maheshwari, and R. Balasubramanian, “Local tetra patterns: a new feature descriptor for content-based image retrieval,” IEEE transactions on image processing, vol. 21, no. 5, pp. 2874–2886, 2012.

[13] K. Song, Y. Yan, Y. Zhao, and C. Liu, “Adjacent evaluation of local bi- nary pattern for texture classification,” Journal of Visual Communication and Image Representation, vol. 33, pp. 323–339, 2015.

[14] L. S. Davis, “Polarograms: a new tool for image texture analysis,” Pattern Recognition, vol. 13, no. 3, pp. 219–223, 1981.

[15] B. S. Manjunath and W.-Y. Ma, “Texture features for browsing and retrieval of image data,” IEEE Transactions on pattern analysis and machine intelligence, vol. 18, no. 8, pp. 837–842, 1996.

[16] R. Porter and N. Canagarajah, “Robust rotation invariant texture classi- fication,” in 1997 IEEE International Conference on Acoustics, Speech, and Signal Processing, vol. 4. IEEE, 1997, pp. 3157–3160.

[17] T. Ojala, T. Maenpaa, M. Pietikainen, J. Viertola, J. Kyllonen, and S. Huovinen, “Outex - new framework for empirical evaluation of tex- ture analysis algorithms,” in 2002 International Conference on Pattern Recognition, vol. 1, 2002, pp. 701–706 vol.1.

[18] E. S. Gemeay, F. A. Alenizi, A. H. Mohammed, M. H. Shakoor, and R. Boostani, “Weighted constraint feature selection of local descriptor for texture image classification,” IEEE Access, vol. 11, pp. 91 673– 91 695, 2023.

[19] Z. Tang, Z. Zhang, J. Feng, W. Chen, K. Zhu, W. Yang, and W. Han, “A fast image stitching algorithm based on texture classification and improved sift,” IEEE Access, vol. 12, pp. 124 183–124 208, 2024.

[20] X. Huang, S. Li, and Y. Wang, “Shape localization based on statistical method using extended local binary pattern,” in Third International Conference on Image and Graphics (ICIG’04), 2004, pp. 184–187.

[21] M. Liu and F. Zhang, “Texture feature extraction and classification based on improved lbp,” in 2023 35th Chinese Control and Decision Conference (CCDC), 2023, pp. 4189–4192.

[22] G. Zhao and M. Pietikainen, “Dynamic texture recognition using local binary patterns with an application to facial expressions,” IEEE Trans- actions on Pattern Analysis and Machine Intelligence, vol. 29, no. 6, pp. 915–928, 2007.

[23] M. H. Shakoor, “Lung tumour detection by fusing extended local binary patterns and weighted orientation of difference from computed tomography,” IET Image Processing, vol. 13, no. 6, pp. 877–884, 2019.

[24] A. Santhoshi and A. Muthukumaravel, “Texture and shape-based feature extraction for colorectal tumor segmentation,” in 2024 10th Interna- tional Conference on Advanced Computing and Communication Systems (ICACCS), vol. 1, 2024, pp. 315–320.

[25] T. Ojala, “Nonparametric texture analysis using simple spatial operators, with applications in visual inspection,” Acta Universitatis Ouluensis, C, vol. 105, 1997.

[26] M. Pietika¨inen, T. Ojala, and Z. Xu, “Rotation-invariant texture classi- fication using feature distributions,” Pattern recognition, vol. 33, no. 1, pp. 43–52, 2000.

[27] D. Huang, Y. Wang, and Y. Wang, “A robust method for near infrared face recognition based on extended local binary pattern,” in Advances in Visual Computing: Third International Symposium, ISVC 2007, Lake Tahoe, NV, USA, November 26-28, 2007, Proceedings, Part II 3. Springer, 2007, pp. 437–446.

[28] Y. Huang, Y. Wang, and T. Tan, “Combining statistics of geometrical and correlative features for 3d face recognition.” in BMVC. Citeseer, 2006, pp. 879–888.

[29] A. Chaudhari and J. Kulkarni, “Cerebral edema segmentation using textural feature,” Biocybernetics and Biomedical Engineering, vol. 39, no. 3, pp. 599–612, 2019.

[30] S. Liao, M. W. Law, and A. C. Chung, “Dominant local binary patterns for texture classification,” IEEE transactions on image processing, vol. 18, no. 5, pp. 1107–1118, 2009.

[31] M. Heikkila¨, M. Pietika¨inen, and C. Schmid, “Description of interest regions with local binary patterns,” Pattern recognition, vol. 42, no. 3, pp. 425–436, 2009.

[32] M. Fritz, E. Hayman, B. Caputo, and J.-O. Eklundh, “The kth-tips database,” 2004.

[33] P. Mallikarjuna, A. T. Targhi, M. Fritz, E. Hayman, B. Caputo, and J.- O. Eklundh, “The kth-tips2 database,” Computational Vision and Active Perception Laboratory, Stockholm, Sweden, vol. 11, p. 12, 2006.

[34] L. Fei-Fei, R. Fergus, and P. Perona, “Learning generative visual models from few training examples: An incremental bayesian approach tested on 101 object categories,” in 2004 conference on computer vision and pattern recognition workshop. IEEE, 2004, pp. 178–178.

[35] K. J. Dana, S. K. Nayar, B. van Ginneken, and J. J. Koenderink, “3d textured surface modeling,” in IEEE Workshop on the Integration of Appearance and Geometric Methods in Object Recognition. Citeseer, 1999, pp. 46–56.

[36] P. B. Textures, “A photographic album for artists and designers,” 1966.