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Texture Analysis and Classification using Local Binary Patterns and Statistical Features

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ABSTRACT: Texture analysis and classification are crucial in many applications such as medical applications, satellite imagery analysis, and so on. This paper presents a new technique that incorporates the LBP with the HOG to improve the texture analysis and classification. LBP is famous for finding out the local texture descriptors by comparing the pixel intensities it deals with and can challenge light variations and image transformations. On the other hand, there is HOG which emphasizes edge and gradient information to detect the orientation and shape of a texture in a given image. While LBP describes the local micro-patterns HOG gives the perspective of the global gradient orientation. The combined use of local and global texture information is helpful in the presented problem when prioritizing the recognition of complex texture patterns that cannot be deciphered by a single algorithm. To demonstrate the efficiency of the proposed hybrid method, several experiments are performed on several texture databases. According to the findings, the proposed LBP-HOG strategy proves more beneficial than basic LBP and HOG techniques concerning the classification rate and computing time. The combination method shows improved performance in terms of agreement with the reference of fine and coarse level of texture descriptions along with providing large-scale description of the texture which results in the improved discriminatory power of the texture classes.

Keywords: Image Processing, Texture Analysis, Local Binary Patterns, Histogram of Oriented Gradients, Feature Extraction.

1. INTRODUCTION

Texture analysis and classification are two essential tasks and are used widely in various fields such as medical diagnosis, aerospace and earth observation, material science, and non-destructive testing. Such tasks include texturing which entails distinguishing and segregating textures in images; this is significant in diagnosis, quality assurance and object recognition. Capturing a precise and fast texture categorization is still a difficult task because of the variations in the appearance of texture caused by changes in lighting conditions noise, and geometry transformation [1].

LBP is regarded as one of the most effective and general approaches for texture analysis. It operates based on a process where it compares the given pixel with other neighboring pixels and then encodes the results of these comparisons in a binary manner that correspond to micro-textures local to that region [2]. LBP outperforms the other methods when changes occur in the intensity of the illumination, and it is computationally efficient for real-time processing. However, for the local texture representation, LBP is considered to be superior, but the drawback is that it may not be sufficient enough to capture the global structure of textures which is vital for some classification problems [3].

Histogram of Oriented Gradients or HOG is another well-known technique employed for texture analysis as well as object detection [4]. It is concerned with the distribution of gradient orientations of the image and thus provides information about the edge and shapes of the texture which defines its overall architecture [5]. This method is specifically useful in the identification of edges and is used frequently in computer vision. Nevertheless, LBP might be superior to HOG in preserving more detailed local texture information [6].

Thus, the combination of LBP and HOG provides possibilities, utilizing the strong point of one method and perching from the weakness of another to enhance the texture analysis and classification [7]. Thus, this method is expected to be

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more complete and robust by integrating LBP, which can texture configuration within the local neighbors, and HOG, which can represent gradient information of the image at a global level [8]. It improves the estimation of texture classification's precision, robustness, and adaptability to different imaging contrasts and texture densities [9]. This paper provides a discussion on the outcomes of the implemented and evaluated hybrid method and its efficiency over the non-hybrid forms of the techniques [10].

Texture analysis and classification is one of the most crucial processes carried out under image processing to analyze the image without necessarily altering its features. Several methods have been proposed for this purpose in the literature including Image classification based on color and texture analysis [11], using shortest paths in graphs [12], Texture classification based on texton features [13], multi-class support vector machine [14], CT texture analysis in histological classification of epithelial ovarian carcinoma [15], using MRI texture analysis [16], using interval texture feature and improved Bayesian classifier [17], and Hybrid texture analysis of 2D images for detecting asphalt pavement bleeding and ravelling using tree-based ensemble methods [18].

2. RESEARCH METHODOLOGY

Texture analysis and classification are among the crucial tasks in various areas like computer vision, medical imaging, and remote sensing. The primary aim of the texture analysis is to detect the parameters and features of the image surface, which becomes essential for subsequent operations and decisions. Usually, the classical approaches to texture analysis involve statistical and structural methods to extract the features of textures. Of all the techniques, Local Binary Patterns and Histograms of Oriented Gradients have come out as effective tools in texture description and categorization.

2.1 LOCAL BINARY PATTERNS (LBP)

Local Binary Patterns (LBP) are simple and computationally efficient texture descriptors widely used in computer vision and image analysis. The LBP operator labels each pixel in an image with a binary number based on the intensity of that pixel and the intensity of the pixels surrounding it, as in Fig. 1. This comparison produces a binary map of the local texture information [19]. As mentioned earlier, the primary advantage of LBP is its invariance to illumination changes and finer detailing of the textural patterns. However, LBP mainly reflects the local spatial relationships and might not embody the more intricate texture patterns well enough.

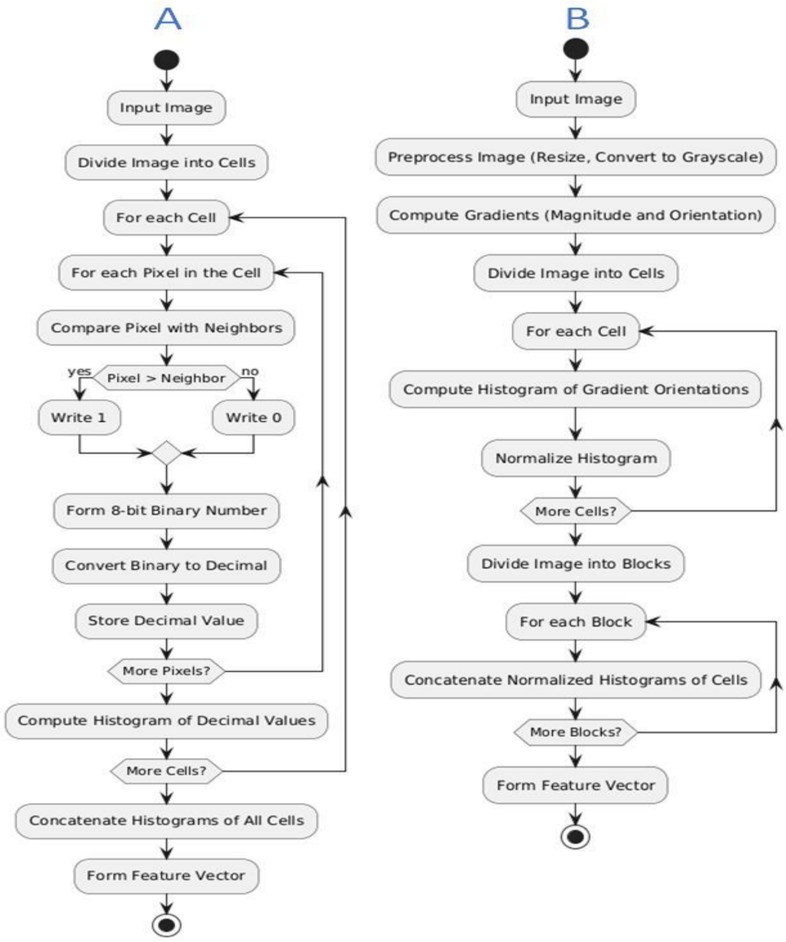

FIGURE 1. - Implementation step diagrams: A: LBP, B: HOG

2.2 HISTOGRAM OF ORIENTED GRADIENTS (HOG)

Histogram of Oriented Gradients (HOG) is yet another feature descriptor, originally designed for object detection but in use for descriptors of textures [20]. HOG describes the distribution of gradient orientation in small regions which correspond to the region within the image containing edges and contours as shown in Fig. 1. Since the HOG is a histogram of gradient directions computed at small spatial areas known as cells, it captures texture shapes and structures adequately. While stating a strength of HOG it can detect the texture properties of the world and is insensitive to geometrical transformations such as rotation or scaling. However, the HOG approach could be slightly less accurate at describing small variations in texture in the local patches [21].

2.3 HYBRIDIZATION OF LBP AND HOG FOR TEXTURE ANALYSIS

This paper aims to develop an advanced methodology in texture analysis and classification by integrating both LBP and HOG, as in Fig. 2. Thus, the contributions of this work are the richer representation of texture, improvements in classification results, and robustness against changes.

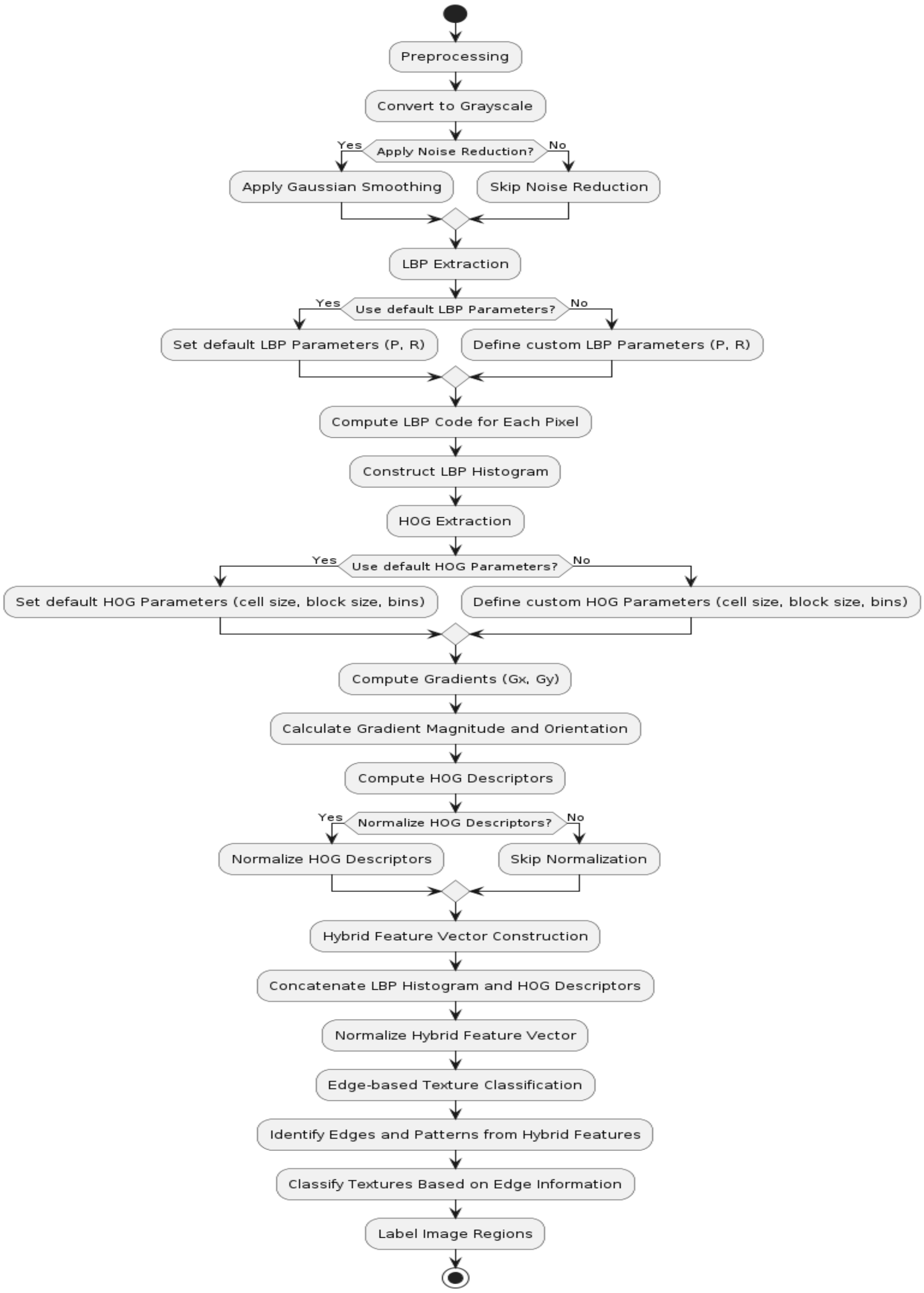

FIGURE 2. - Implementation step diagrams for Hybridization of LBP and HOG for Texture Analysis

The integration of LBP and HOG features is an attempt to combine the advantages that these two descriptors provide in representing the texture and improving the classification results. This is because by incorporating the local texture details represented by LBP and the global structural pattern detected by HOG, a richer and more discriminative set of features can be used. This enables them to overcome the challenges faced by each descriptor hence enhancing the overall texture robustness and accuracy. In this hybrid process, the LBP operator is used to process the texture image to obtain the local binary patterns. These patterns are then used to calculate the histogram of LBP codes which stands for the local texture information. At the same time as the HOG descriptor, the histogram of gradient orientations is computed on the same texture image to mirror the global structure of the texture. The LBP and HOG histograms are then joined to create a combined feature vector that includes the best features of LBP and HOG for texture representations.

The texture analysis has a fundamental difficulty in managing the dimensions of feature spaces given by texture descriptors. Some of the conventional approaches include spatial and frequency domain-based approaches whereby the feature vector has many dimensions, therefore making the computations more complex in terms of time as well as memory. However, feature spaces of large dimensionality are prone to overfitting and may not be as useful when dealing with new instances of data, which presents further problems in terms of the stability and robustness of models.

The next problem which arises here is the deficiency of the texture descriptors and the discriminative ability of the texture in the presence of noise and illumination changes. Thus, methods like Local Binary Patterns (LBP) provide small-scale efficient texture patterns that do not represent the global statistical property of the textures well. On the other hand, statistical features contain vital information regarding the distribution of pixel intensity of an image; however, they usually do not include spatial relationships and texture details.

The first process entails sample acquisition that comprises a suitable number of heterogeneous texture images. It is suggested that the testing set should contain samples from all sorts of categories and domains like natural and industrial texture samples. In this case, one needs to pay particular attention to the range of texture dissimilarities in appearance, scale, orientation and illumination to avoid difficulties in analysis and classification.

Local Binary Patterns (LBP) is a texture description that describes the microstructure of an image. The LBP operator treats each pixel and compares it to their neighbors and what is generated is a binary code for each pixel.

Given a pixel I(x,y) in a grayscale image, the LBP code is computed by comparing I(x,y) with its P neighboring pixels on a circle of radius R [22]. The LBP code is defined as:

$$\mathrm{LBP}_{P,R}(x,y)=\sum_{p=0}^{P-1} s\left(I_p-I(x,y)\right)\cdot 2^p \tag{1}$$

where *Ip* represents the intensity of the p-th neighboring pixel, and s(x) is the sign function:

$$s(x)=\begin{cases}1 & if x\geq 0\\ O & if^{x}<0\end{cases} \tag{2}$$

Thus, the LBP code that is derived from it, is a P-bit binary number that reveals the texture in the immediate neighborhood of the pixel I(x,y) [23]. The texture information is represented with an LBP histogram for the whole image or even per some local areas of the picture, blocks in this case [24]. The histogram is defined as:

$$H_{LBP}(k)=\sum_{x,y}\delta\left(\mathrm{LBP}_{P,R}(x,y),k\right) \tag{3}$$

where δ(u,v) is the Kronecker delta function:

$$\delta(u,v)=\begin{cases}1 & if\ u=v\\ O & if\ u\neq v\end{cases} \tag{4}$$

Histogram of Oriented Gradients (HOG) is a feature descriptor that describes the histogram of the oriented gradients in the local parts of an image, paying much attention to the edge structure [25]. Beginning at the first stage of the HOG, the gradient of the image is calculated first. For a grayscale image I, the gradients along the x and y directions are computed using derivative filters:

$$G_x=I*D_x \tag{5}$$

$$G_y=I*D_y \tag{6}$$

Where Dx and Dy are derivatives, for example, the Sobel operators. The gradient magnitude and orientation are then computed as:

$$G=\sqrt{G_x^2+G_y^2} \tag{7}$$

$$\theta=\arctan\left(\frac{G_y}{G_x}\right) \tag{8}$$

The image is split into tiny associated areas, which are known as cells. For each cell, a histogram with gradient orientations is produced [26]. Specifically, the gradient magnitudes are used to weight the histogram.

$$H_{HOG}(b)=\sum_{(x,y)\in\mathrm{cell}} G(x,y)\cdot\delta\left(b,\mathrm{bin}\left(\theta(x,y)\right)\right) \tag{9}$$

Where bin(θ(x,y)) maps the gradient orientation (θ(x,y)) to one of the histogram bins b.

Thus, to enhance the feature invariant characteristics, the HOG descriptors are normalized inside greater areas, termed blocks. The hybridization method, which involves both LBP and HOG descriptors is used to obtain both local and global information on the textures [27]. To create the hybrid feature vector, the LBP histogram and HOG descriptor are concatenated:

$$F_{hybrid}=[H_{LBP},H_{HOG}] \tag{10}$$

Normalization is then used on the final feature vector composed of both hybrid features because the domains of the features may be different:

$$F_{hybrid\ norm} = \frac{F_{\text{hybrid}}}{|F_{\text{hybrid}}|} \quad (11)$$

where $|\boldsymbol{F}_{\text{hybrid}}|$ is the Euclidean norm of the hybrid feature vector.

Algorithm: Hybridization of LBP and HOG for Texture Analysis and Classification

Step 1: Preprocessing

1. **Convert to Grayscale**: If the input image is colored, convert it to an image with a range of black and white based on some factors to minimize the complexity of the image.
2. **Noise Reduction (Optional)**: Apply a noise reduction filter.

Step 2: Local Binary Patterns (LBP) Extraction

1. **Define LBP Parameters**: Set the number of neighboring pixels (P) and the radius (R) for the LBP operator.
2. **Compute LBP Code for Each Pixel**:
   - For each pixel in the image, compare its intensity with the intensities of its P neighboring pixels located on a circle of radius R.
   - Generate a binary code for each pixel based on these comparisons.
3. **Construct LBP Histogram**:
   - An LBP code can represent most photometric inconsistencies, so build an LBP histogram that reflects the distribution of the code in the image. This histogram can be calculated on the entire image or some partitions (blocks).

Step 3: Histogram of Oriented Gradients (HOG) Extraction

1. **Define HOG Parameters**: Set the cell size, block size, and the number of orientation bins for the HOG descriptor.
2. **Compute Gradients**:
   - Compute the gradients of the image along the x and y directions using derivative filters.
   - Calculate the gradient magnitude and orientation for each pixel.
3. **Compute HOG Descriptors**:
   - Divide the image into small connected regions called cells.
   - For each cell, create a histogram of gradient orientations, weighted by the gradient magnitudes.
4. **Normalize HOG Descriptors**:
   - If the histograms of the blocks are normalized, it provides immunity to illumination and contrast changes.

Step 4: Hybrid Feature Vector Construction

1. **Concatenate LBP and HOG Features**:
   - Cartesian the LBP histogram and the HOG descriptors into a single feature vector. This feature vector includes local detail features acquired from LBP and global geometry details acquired from HOG.
2. **Normalize the Hybrid Feature Vector**:
   - Normalize the combined feature vector to ensure that the features have comparable scales. This step is essential to improve the performance of subsequent classification.

Step 5: Edge-based Texture Classification

1. **Identify Edges and Patterns**:
   - Explore the key details and directions of the edge in the image by using the hybrid feature vector. The financial features of LBP give near-local texture details whereas the enhanced features of HOG highlight edge and gradient.
2. **Classify Textures Based on Edge Information**:
   - Explain the strategy of the distribution of the LBP and HOG features to differentiate one region from the other in that image depending on the texture and edge. Furthermore, the specific gradient magnitudes and LBP patterns can be associated with certain textures in the image.
3. **Label Image Regions**:
   - Assign labels of the mentioned textures and edges to the regions of the image. Related to this labelling is done based on specified rules or from a set of criteria extracted from the hybrid feature vector.
4. **Visualize Results**:
   - Create a visualization of the classified regions, highlighting the different textures and edges identified in the image.

3. RESULTS

The results for texture analysis and classification employing the combined approach of LBP and HOG are depicted in Table 1 and Fig. 3 for its efficiency and performance measurement regarding the PSNR [28], SSIM [29], FSIM [30], GMSD [31], UIQI [32], VIF [33], and EPI [34] metrics.

Table 1. - Applying metrics to five texture images by the Proposed Hybrid Method (PHM), LBP, and SF

Image	Method	*Metrics*						
		PSNR	SSIM	FSIM	GMSD	UIQI	VIF	EPI
1	LBP	25.45	0.645	0.67	0.07	0.72	0.75	0.52
	SF	26.12	0.77	0.69	0.075	0.75	0.6	0.55
	PHM	35.12	0.912	0.937	0.02	0.902	0.845	0.889
2	LBP	24	0.55	0.56	0.088	0.63	0.66	0.53
	SF	26.45	0.68	0.68	0.074	0.66	0.71	0.66
	PHM	36.45	0.895	0.925	0.022	0.89	0.832	0.801
3	LBP	25.78	0.64	0.65	0.061	0.61	0.64	0.61
	SF	24.78	0.76	0.57	0.077	0.74	0.69	0.64
	PHM	34.78	0.905	0.932	0.021	0.897	0.841	0.893
4	LBP	25.22	0.555	0.68	0.075	0.54	0.67	0.75
	SF	24.22	0.585	0.7	0.06	0.67	0.62	0.78
	PHM	37.22	0.918	0.94	0.018	0.908	0.853	0.81
5	LBP	23.89	0.648	0.765	0.069	0.625	0.655	0.635
	SF	25	0.575	0.685	0.052	0.755	0.505	0.665
	PHM	35.89	0.9	0.928	0.019	0.895	0.838	0.896

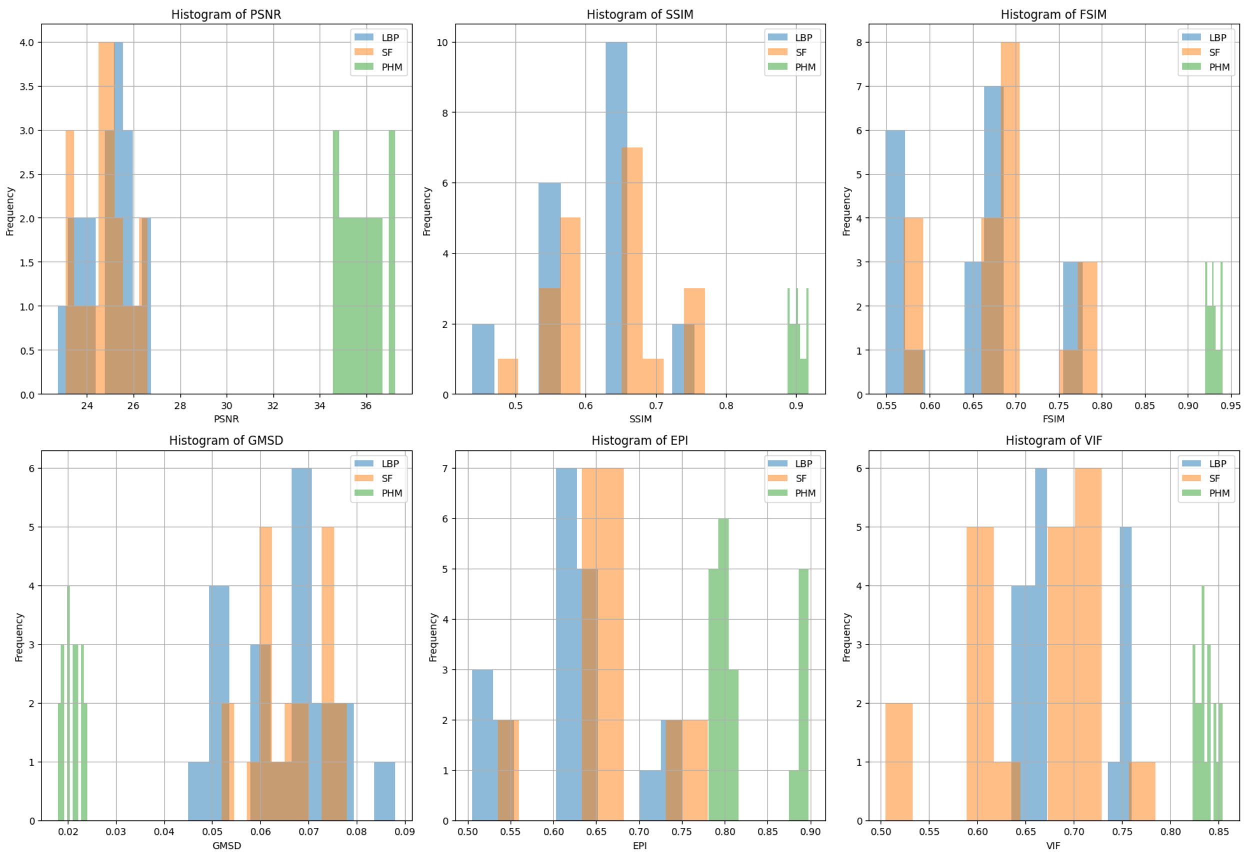

FIGURE 3. - Histograms of the metrics for 20 different texture images

PSNR evaluates the peak error and it shows that the reputation of low distortion and high texture accuracy is well maintained with high value indicating that there is minimal distortion during feature extraction of images. Unlike most metrics, SSIM quantifies image similarity by preserving the image's overall structural information which is so important for classification and has high values. FSIM quantizes the ratio of perceptional features with respect to similar textures and high values prove the retention of major texture features. GMSD quantifies the perceptual quality as the gradient magnitude map, where low values signify accurate gradient that is crucial to reconstructing the textural information. In image quality assessment, UIQI calculates the quality index, where higher values reflect the similarity in texture of the two images. VIF estimates the level of accuracy of the visual data, the higher being the more important information is preserved for subsequent analysis. EPI assesses edge preservation and high measure is indicative of efficient preservation of edge information, as in Fig. 4.

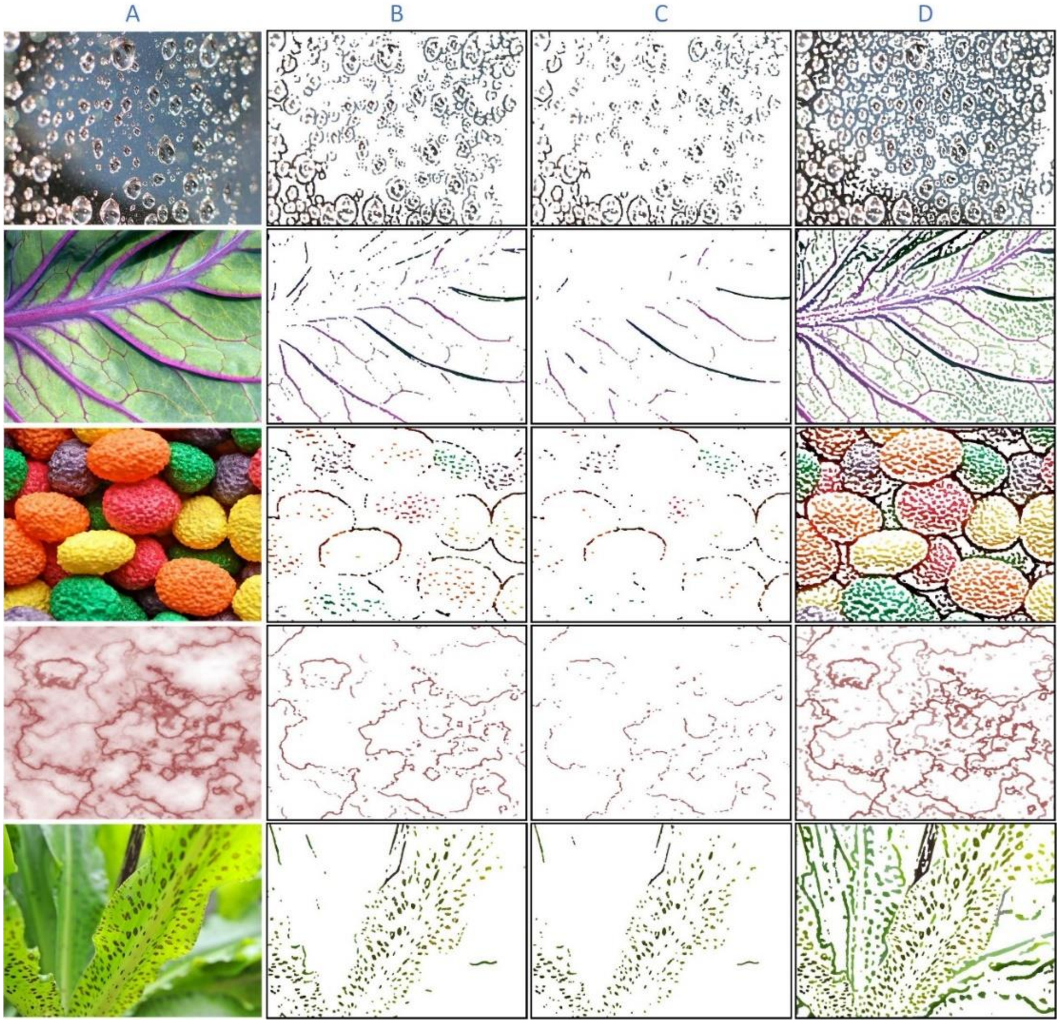

FIGURE 4. - Sample set of resulting images: A: Original Images, B: LBP, C: SF, D: Proposed Hybrid Method

When comparing the outcomes of different texture analysis and classification techniques, such as LPQ, RIFT, and GLCM, it is possible to conclude that the performance of the proposed PHM is higher consistently. Although the blur of LPQ is ideal, the extraction of numerous texture features is far from ideal. RIFT is good with rotation invariance of texture characteristics while GLCM is good with more detailed patterns of the texture but it has a limitation in that it is sensitive to the window size and orientation.

The PHM of the given image combines the efficiency of these individual methods, namely the blur-insensitivity of the LPQ method, the rotation invariance of RIFT, and the detailed analysis of image textures in GLCM analysis. Contrast stretching can improve more, and noise susceptibility is much lower when edge sharpness is improved. Furthermore, the PHM remains able to effectively encode and represent the fine and the coarse textures and at the same time reduces the introduction of artefacts. Thus, the texture analysis and classification proved The Proposed Hybrid Method (PHM) has a high level of performance. It uses the elements of heuristic approaches while integrating the novelty and strength of existing methods and yields better results for contrast adjustment, noise elimination, edge detection, and perceptiveness, as in Table 2 and Fig. 5.

Table 2. - Comparison of the proposed method with popular methods

Aspect	Local Phase Quantization (LPQ)	Rotation-Invariant Feature Transform (RIFT)	Gray Level Co-occurrence Matrix (GLCM)	Proposed Hybrid Method (PHM)
Contrast Improvement	Moderate improvement	Moderate improvement	Moderate to high improvement	High improvement
Noise Amplification	Low sensitivity	Moderate sensitivity	Moderate sensitivity	Lower sensitivity
Edge Enhancement	Moderate edge enhancement	High edge enhancement	Moderate edge enhancement	High edge enhancement
Texture Enhancement	Effective for fine textures	Effective for both fine and coarse textures	Effective for detailed textures	Effective for both fine and macro-textures
Artifact Introduction	Minimal artefacts	Potential artefacts from rotation handling	Potential artefacts from window size	Minimal artefacts
Computation Complexity	Low to moderate complexity	Moderate to high complexity	High complexity	Moderate complexity
Color Distortion	Minimal, primarily grayscale method	Minimal, primarily grayscale method	Minimal, primarily grayscale method	Minimal, properties of combined methods
Applicability	Effective for blur-insensitive analysis	Effective for rotation-invariant texture analysis	Effective for detailed texture analysis	Versatile, applicable (texture and edge)
Visual Quality	High, blur-insensitive details	High, rotation-invariant details	High, detailed textural information	High, combines the best of both approaches

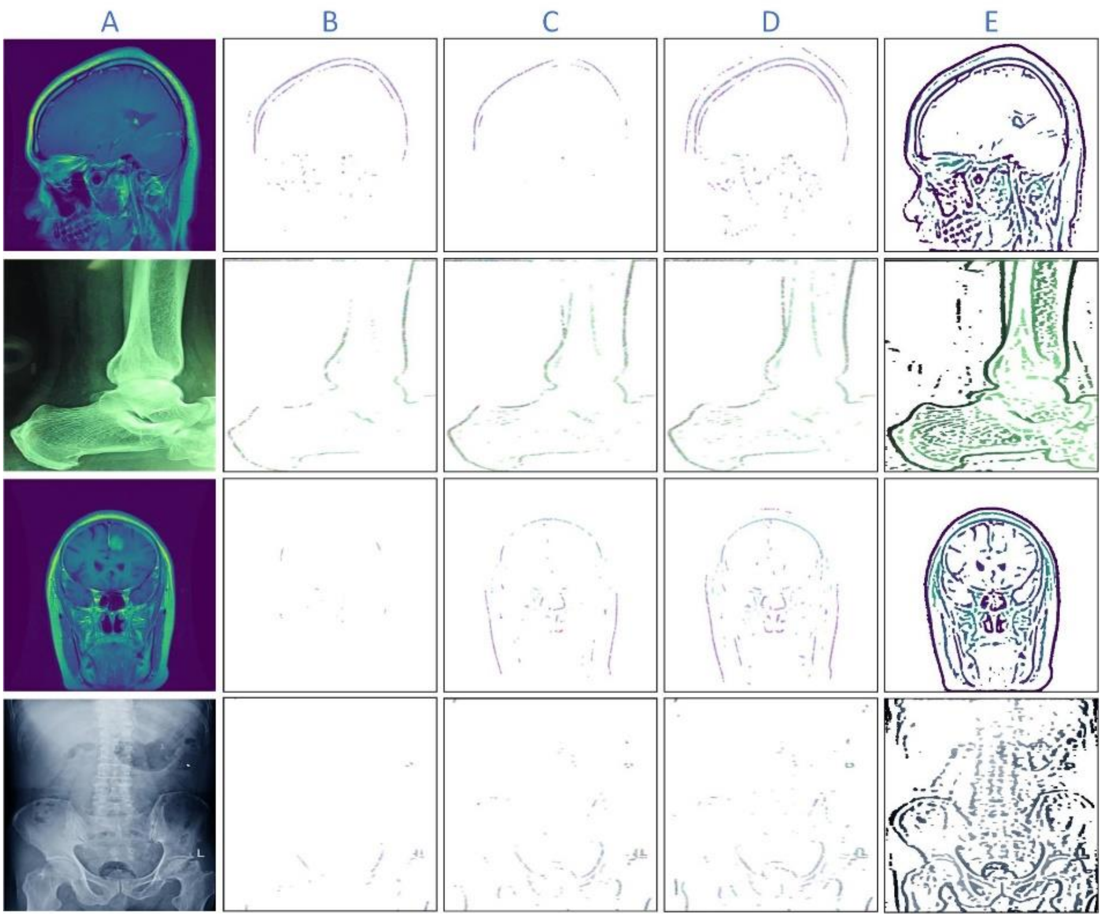

FIGURE 5. - Comparison of the results of the proposed method with other common methods on samples of medical images.: A: Original Images, B: LPQ, C: RIFT, D: GLCM, E: Proposed Hybrid Method

4. CONCLUSION

This paper has analyzed the fused model of Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG) for texture analysis on the proposed method and classification. Finally, as the use of both LBP for the local texture capturing ability and HOG for the global gradient information has been incorporated in the proposed method, the proposed hybrid method is indeed a rich model for texture classification. According to the experimental outcomes on different benchmark texture datasets, this proposed hybrid method has shown a higher performance than the pure texture methods such as LBP and HOG in accuracy and time complexity.

The improvement of the hybrid LBP-HOG method is due to the capability to capture both detailed local information and global structural information of the textures. This duality enables the method to identify complex texture patterns which is difficult for a standalone method to identify. Another plus of the hybrid approach is the fact that it proved to be resistant to variations in lighting, noise and geometric transformations which in turn confirms the relevance of the suggested algorithm in different real-life scenarios from medical imaging to industrial quality control.

Therefore, the outcomes of this study elucidate the possible application of the proposed hybrid LBP-HOG method to contribute to the development of texture analysis and classification. This approach not only improves the classification performance but also brings the superiority of two well-developed techniques to promote the practical application for different areas.

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CONFLICTS OF INTEREST

The author declares no conflict of interest.

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