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Medical Cancer Diagnosis Using Texture Image Analysis

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Abstract - In computer vision applications including object recognition, surface defect detection, pattern recognition, medical picture analysis, etc., texture analysis is crucial. The spatial organisation of pixel intensities in a picture that repeats frequently over the entire image or in specific sections is referred to as the texture. The primary phrase used to describe the concepts or things in an image is its texture. Since then, numerous strategies have been put forth to adequately represent texture images. The four main categories of texture analysis techniques are statistical, structural, model-based, and transform-based techniques. The human visual system primarily uses texture, colour, and shape to identify the contents of images. First and foremost, effective and updated texture analysis operators are described in depth in this study. Next, some cutting-edge techniques for using texture analysis in medical applications and illness diagnostics are presented. In terms of accuracy, dataset, applicability, etc., various methodologies are contrasted. The effectiveness of discriminating, computing complexity, and resilience to difficulties like noise, rotation, etc. are the main considerations in all of the approaches that have survived. Results show that texture features, either alone or in combination with other feature sets like depth, colour, or shape features, provide high accuracy in classifying medical images.

Keywords: Texture Image, Tactile texture , Feature Extraction, Medical Image Analysis, Texture image analysis.

1. INTRODUCTION

The natural world is full of texture; any observable object's surface has some degree of texture. On both man-made and natural things, such as those made of wood, plants, materials, and skin, a variety of textures can be seen. The word "texture" often refers to an object's surface features and appearance that are determined by the size, shape, density, arrangement, and proportion of its fundamental components. It is common to use terms like smooth or rough, soft or hard, coarse or fine, matt or glossy, etc. to describe textures. Both the tactile and the visual aspects of the texture are distinguishable. Visual texture relates to viewing the shape or contents of the image, and tactile texture refers to the palpable feel of a surface [1]. The detection of texture in a human vision system is simple, but image processing and the machine vision domain are more difficult. The texture in image processing is a function of the spatial variation in pixel brightness intensity [2]. The texture depicts the changes of each level, which rates the regularity, smoothness, coarseness, and other qualities of each surface in relation to one another. Pictures with a specified pattern of distribution and dispersion of the intensity of the pixel illumination are referred to as "textural images" in image processing and machine vision [2]. In Figures 1 and 2, examples of both natural and man-made textures are displayed.

Fig -1: Examples of Natural Textures

Fig -2: Examples of Artificial Regular Textures

A.TEXTURE ANALYSIS

The main problems behind texture analysis are discussed in Figure 3 [3].

1. Texture Classification
2. Texture Segmentation
3. Texture Synthesis
4. Texture Shape

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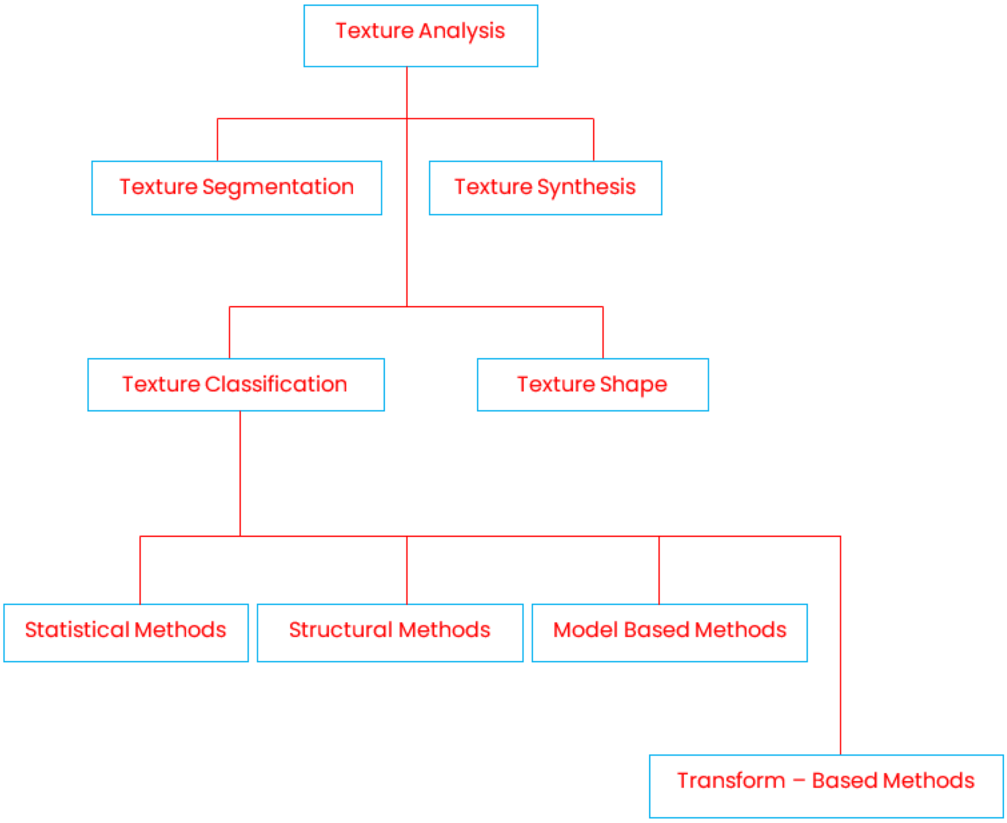

Fig -3: General Idea behind Texture Analysis

Texture Segmentation

It seeks to divide a textured image into a number of regions with comparable patterns. Applications like seismic image analysis, biological image analysis, and aerial image analysis would all benefit greatly from an effective and economical texture segmentation method, as will the automation of industrial applications.

Texture Synthesis

It is a subject of computer graphics study and is applied in a variety of industries, including digital image editing, 3D computer graphics, and post-production of motion pictures. Texture synthesis can be used to extend small images, fill in gaps in images (like in painting), and make large, non-repetitive backgrounds.
Texture Shape

The more detail employed in the usage of texture (such as the texture of leaves, skin, etc.), the more realistic a work of art might look. Texture is sometimes used to give the illusion of depth or make a piece seem more genuine. A scene's atmosphere can be created in part by texture.

Texture Classification

One of the key areas of texture analysis is texture classification, whose major objective is to offer labels for classifying textural images. Texture classification involves placing an ambiguous sample image into a certain texture class.

Statistical Methods
A collection of statistics are derived from the distributions of the local features using statistical texture analysis, which computes local features in parallel at each place in a texture image. The combination of intensities at specific locations in relation to each point in the image defines the local feature.
Structural Methods

In structural approaches, the texture is viewed as a linear and structured phenomenon. The structure of distinct texture elements, such as parallel lines with regular spacing, is what is referred to as texture in techniques for structural texture analysis.

Model -Based Methods
The texture-based approach uses simultaneous Markov Random Field Texture Models, Multifractal Analysis in Multi-Orientation and Wavelet Pyramid.

(iv) Transform -Based Methods
Wavelet channel combining, the Binary Gabor Pattern, the LL channel filter bank, the GLCM and Gabor Filters, the Gabor and LBP, the wavelet transform and GLCM, the SVD and DWT domains, and the Skeleton primitive are all included.

B.TEXTURE ANALYSIS TECHNIQUES

The analysis of image texture has been done using a variety of ways up to this point. In order to apply machine learning algorithms for object recognition, the majority of the methods currently available in this field attempt to identify the repeating pattern in the image and extract it in the form of numerical features[4]. Finding flaws [5, quality assurance [6, medical diagnosis [7], etc. Picture histogram analysis is one of the easiest techniques for extracting image texture properties [8]. An image histogram is a two-dimensional graph where the vertical axis represents the number of pixels in the image that have the specified grey level and the x-axis represents the image's overall grey level.
As a result, each bin (column) in the normalised histogram displays the likelihood that the desired grey level would appear in the input image. Since the normalised histogram of the image is a statistical and probabilistic graph, many features that each define a particular attribute (property) of the graph can be retrieved from it. Following are a few of the well-liked texture features that can be derived from a histogram:

$$\text{Mean:} \quad f_1 = \sum_{i=0}^{G-1} iP(i) \tag{1}$$

$$\text{Skewness:} \quad f_2 = \sigma^{-3} \sum_{i=0}^{G-1} (i - f_1)^3 p(i) \tag{2}$$

$$\text{Kurtosis=} \quad f_3 = \sigma^{-4} \sum_{i=0}^{G-1} (i - f_1)^4 p(i) - 3 \tag{3}$$

$$\text{Energy =} \quad f_4 = \sum_{i=0}^{G-1} [p(i)]^2 \tag{4}$$

$$\text{Entropy=} \quad f_5 = \sum_{i=0}^{G-1} p(i) \log_2 [p(i)] \tag{5}$$

where P(i) displays the likelihood that grey levels I will appear in the image (the height of ith bin in the normalised histogram). Additionally, G is the total number of possible grey levels in the image, which in images with an 8-bit format can be thought of as 256. One of the most effective image texture analysis operators is gray-level Co-occurrence matrices (GLCM) [9]. The number of occurrences of the grey level "x" under the particular connection (d) with the grey level "y" in the image is represented by each cell in the co-occurrence matrix with (x, y) coordinates. The normalised co-occurrence matrix is created by multiplying all of the GLCM's cells by the total number of pixels.

An example of the GLCM process is shown in Figure 4.

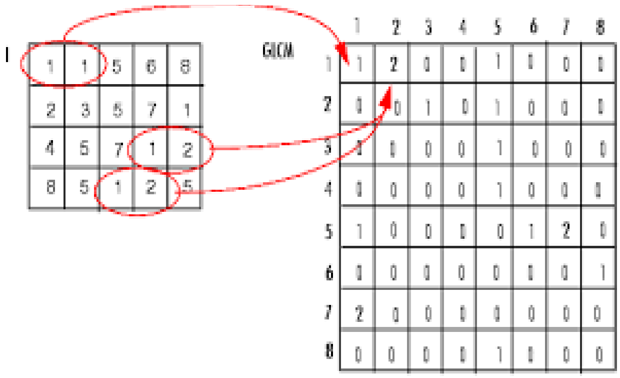

Fig -4: An example of the GLCM Process Model

Another statistical and probabilistic operator is the GLCM. As a result, the texture of the image can be represented by extracting statistical data from it. The following are some texture features that can be retrieved from the GLCM.

Feature	Description	
Energy (ENR)	$ENR = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} G(i,j)^2$	(6)
Entropy (ENT)	$ENT = -\sum_{i=0}^{n-1}\sum_{j=0}^{n-1} G(i,j)\ln[G(i,j)]$	(7)
Contrast (CON)	$CON = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} G(i,j)(i-j)^2$	(8)
Difference entropy (DENT)	$DENT = -\sum_{i=0}^{n-1} G_{x-y}(i)\ln[G_{x-y}(i)]$	(9)
Difference variance (DVAR)	$DVAR = -\sum_{i=0}^{n-1} G_{x-y}(i)(i-DENT)^2$	(10)
Maximum probability (MAXP)	$MAXP = MAX_{i,j}G(i,j)$	(11)
Sum entropy (SENT)	$SENT = -\sum_{i=2}^{2n} G_{x+y}(i)\ln[G_{x+y}(i)]$	(12)
Sum average (SVAR)	$SVAR = \sum_{i=0}^{n-1} iG_{x+y}(i)$	(13)
Homogeneity (HOM)	$HOM = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} G(i,j)/(1+(i-j)^2$	(14)
Correlation (COR)	$COR = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} \frac{G(i,j)[(i-\mu_x)(j-\mu_y)}{\sigma_x\sigma_y}$	(15)

One of the most often utilised operators in the study of image texture is the local binary pattern (LBP) [10]. Based on the correlation between a pixel's intensity and that of its neighbours, this operator creates a binary pattern for each pixel in the image. In order to use this operator, the pixel in question must first have a

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neighbourhood, with the desired pixel being located in the neighborhood's centre. The intensity of each neighbour is then compared to the neighborhood's centre; if the intensity of the neighbour is higher than the centre, a bit representing that point is indicated, otherwise a bit representing that point is indicated.

A binary pattern is then generated around each pixel. The resulting binary pattern will have 8 bits and can be translated to a number in the base ten range if there are eight neighbours. Finally, the LBP for each pixel has a numerical value between 0 and 255 if there are 8 neighbours. A histogram of LBP values can be created and utilised for feature extraction once the local binary pattern operator has been applied to the entire image. Figure 5 illustrates the LBP procedure as an example.

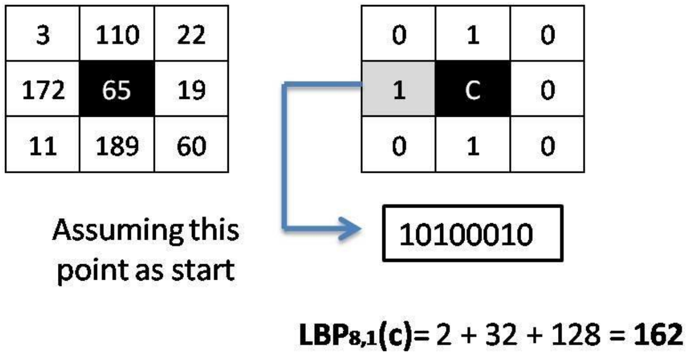

Fig -5: An example of the LBP Process

C. FEATURE EXTRACTION METHOD FOR CATEGORIZING TEXTURES

Texture categorization is the process of placing a sample image in a texture group that has already been established. A two-step method is typically included in this classification.

A) The feature extraction phase, the first stage, is when textural properties are extracted. The objective is to develop a model for each texture that is present on the training platform.

B) The classification phase, the second stage:

In this phase, the test sample picture texture is first examined using the same method as in the preceding stage. Next, a classification algorithm is used to compare the test image's extraction characteristics to the train imagery and identify the test image's class.

D. FEATURE EXTRACTION PHASE

Making models for each of the textures present in educational photography is the initial step in the extraction of texture features. Discrete histograms, empirical distributions, and texture features like contrast, spatial organisation, direction, etc. can all be considered as extractive features at this point. These characteristics are applied to categorization instruction.

E. CLASSIFICATION PHASE

By comparing the vector of the extracted features from the educational phase with the vector of the selection test phase characteristics, the appropriate class for each image is selected in the second stage, where the texture classification is based on the use of machine learning algorithms with monitoring or classification algorithms. For every image that is undergoing testing, this procedure is repeated. The recognition rate, which indicates the effectiveness of the implemented method, is calculated after the estimated classes have been modified to test with their actual classes. Each algorithm's recognition rate is then used to compare the effectiveness of its algorithm with other available methods.

2. LITERATURE REVIEW

One-dimensional local binary patterns, which are applied in the field of visual inspection systems, were first proposed by Tajeripour et al. [11]. A new feature extraction approach called as the Modified local binary patterns was introduced by Ojala et al. [12] from locally extracted binary patterns (MLBP). Tan et al. [13] proposed the operator of local ternary patterns in this context and characterised the difference in pixel intensities based on three components (-1, 1, and 0). (LTP).

3. PROPOSED METHODOLOGY IN MEDICAL ANALYSIS

A. Breast Cancer

Figure 6 depicts the broad framework of the suggested method. To extract textural information, four separate LBP histograms are built using different thresholds, such as the centre intensity, mean of the neighbours, the maximum intensity between neighbours, and the lower value.

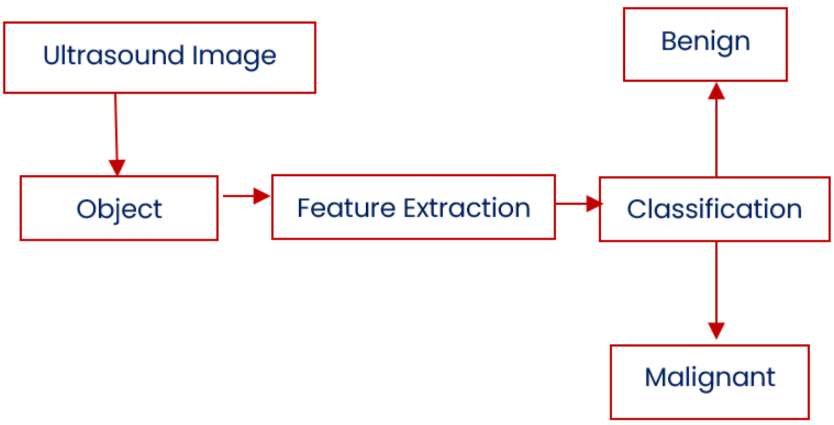

Fig -6: Framework of Breast Cancer Diagnosis

LBP and Curvelet transform were combined by Bruno et al. [14] to classify breast cancer. Figure 7 displays the primary block diagram of the suggested method.

1) The curvelet domain is applied to every breast ultrasound image.

2) Different scales of altered images are used for LBP.

3) Finally, feature selection technique is utilised to reduce complexity.

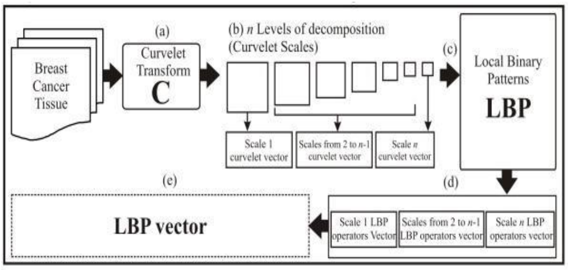

Fig -7: Block diagram of the proposed Methodology

B. Cervical Cancer

In cervix cells, texture properties are crucial for cytoplasm analysis. For the purpose of diagnosing cervical cancer, modified uniform local ternary patterns (MULTP) are employed as feature extractors and multi-layer perceptrons (MLP) as classifiers. The process is divided into two stages: feature extraction and classification.

1) From the input single cell image, popular handcrafted texture characteristics are retrieved, including Law's, discrete wavelet transform (DWT), local binary patterns (LBP), and gray-level co-occurrence matrixes (GLCM).

2) For the classification stage, a linear support vector machine (SVM) is employed.

For the purpose of classifying pap smears, texture statistical features are retrieved from the histogram using a combination of time-series data and global significant value (GSV) information [15]. An accurate tool for detecting cervical cancer by human professionals is a Pap smear image.

C. Lung Cancer

Another area where texture features can be extensively employed is in the segmentation and detection of lung cancer tumors. Lung cancer categorization makes use of the fundamental GLCM operator. The accuracy of the final categorization is increased by performing GLCM in various directions. To identify lung cancer in chest CT scan pictures, textural features are combined with active contours and super pixel techniques.

D. Skin Cancer

One of the skin conditions whose early detection can improve the effectiveness of treatment is lupus erythematosus. The analysis of a patient's skin can be done extremely well using texture features. Texture operators are used in some investigations on cell and bacteriophage image analysis.

4. RESULTS AND DISCUSSION

Brain tumour identification with Magnetic Resonance Imaging (MRI) is facilitated by biomedical image processing. The fundamental goal of is to divide the brain into two groups: tumor-affected and healthy brains. Region of Interest (ROI) segmentation employs contourlet transformation. Next, GLRLM and Center-Symmetric Local Binary Patterns are used for feature extraction (CSLBP).. Examined is the impact of image texture analysis in different medical applications.

4.1 Dataset

DDSM Dataset

There are 2,620 digitised film mammography studies in the DDSM database. It includes instances with certified pathology data for normal, benign, and cancerous conditions. The DDSM is a helpful tool in the design and testing of decision support systems due to the size of the database and ground truth checking.

Herlev Dataset

The majority of the currently used algorithms have been tested on the single cell picture dataset HERLEV. Blood clot and inflammatory cells are overlapping and weakly stained in the Real dataset.

Self-collected Dataset

Microsoft Kinect sensor v1.0, which was mounted 1.4 metres above the ground, was used to gather the data for this dataset. The participants in the self-collected dataset range in age from 20 to 36, as well as in height (1.70–1.81 m) and gender (four male and one female volunteer).

Dataset for DermIS

Datasets are groups of information. Numerous datasets from BioGPS can be browsed and quickly seen in our interactive data chart. Table 1 displays the outcome based on the problem type, the texture operator type, the dataset, and the classification accuracy.

Table -1: Texture Operators in Medical Applications [15][16][17]

Problem	Operator	Dataset	Accuracy
Breast Cancer	LBP & Curvelet	DDSM	94
Cervical Cancer	GLCM	Herlev	83.4
Cervical Cancer	LBP	Herlev	84.8
Lung Cancer	GLCM	Self-collected	81.8
Skin Cancer	LBP	DermIS	87.35

5. CONCLUSION

For identifying and examining both pronounced and subtle textures in multi-modality medical images, texture analysis techniques are helpful. The ability of each feature to distinguish between textures must be carefully considered for practical implementation. To lessen the impact of highly correlated features and features with weak discriminative power on the overall classification, this is crucial. Texture classification techniques are divided into four major groups, some of which are special. Most techniques fall under the statistical and transform-based categories, or a combination of these categories.

REFERENCES

[1] Tuceryan, M., and Jain, A.K. (1993). Texture analysis, in Handbook of pattern recognition and computer vision. World Scientific Publisher, 235-276.

[2] Eichkitz, C. G., Davies, J., Amtmann, J., Schreilechner, M.G., and De Groot, P. (2015). Grey level co-occurrence matrix and its application to seismic data, First Break, 33(3), 71-77.
[3] Holub, O., & Ferreira, S. T. (2006). Quantitative histogram analysis of images. Computer physics communications, 175(9), 620-623.
[4] Manjunath, B.S., and Ma, W.Y. (1996). Texture features for browsing and retrieval of image data. IEEE Transactions on pattern analysis and machine intelligence, 18(8), 837-842.
[5] Giveki, D. (2021). Robust moving object detection based on fusing Atanassov's Intuitionistic 3D Fuzzy Histon Roughness Index and texture features. International Journal of Approximate Reasoning, 135, 1-20.
[6] Ojala, T., Pietikäinen, M., & Mäenpää, T. (2000, June). Gray scale and rotation invariant texture classification with local binary patterns. In European conference on computer vision (pp. 404-420). Springer, Berlin, Heidelberg.
[7] Tajeripour, F., & Fekri-Ershad, S. (2014). Developing a novel approach for stone porosity computing using modified local binary patterns and single scale retinex. Arabian Journal for Science and engineering, 39(2), 875-889.
[8] Chen, Y., Ding, Y., Zhao, F., Zhang, E., Wu, Z., & Shao, L. (2021). Surface defect detection methods for industrial products: A review. Applied Sciences, 11(16), 7657.
[9] Ojala, T., Pietikainen, M., & Maenpaa, T. (2002). Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE Transactions on pattern analysis and machine intelligence, 24(7), 971-987.
[10] Bruno, D. O. T., Do Nascimento, M. Z., Ramos, R. P., Batista, V. R., Neves, L. A., & Martins, A. S. (2016). LBP operators on curvelet coefficients as an algorithm to describe texture in breast cancer tissues. Expert Systems with Applications, 55, 329-340.
[11] Arya, M., Mittal, N., & Singh, G. (2018). Texture-based feature extraction of smear images for the detection of cervical cancer. IET Computer Vision, 12(8), 1049-1059.
[12] Almansour, E., & Jaffar, M. A. (2016). Classification of Dermoscopic skin cancer images using color and hybrid texture features. IJCSNS Int J Comput Sci Netw Secur, 16(4), 135-139.
[13] Bruno, D. O. T., Do Nascimento, M. Z., Ramos, R. P., Batista, V. R., Neves, L. A., & Martins, A. S. (2016). LBP operators on curvelet coefficients as an algorithm to describe texture in breast cancer tissues. Expert Systems with Applications, 55, 329-340.
[14] Althubiti, S. A., Paul, S., Mohanty, R., Mohanty, S. N., Alenezi, F., & Polat, K. (2022). Ensemble Learning Framework with GLCM Texture Extraction for Early Detection of Lung Cancer on CT Images. Computational and Mathematical Methods in Medicine, 2022.
[15] Tan, X., & Triggs, B. (2010). Enhanced local texture feature sets for face recognition under difficult lighting conditions. IEEE transactions on image processing, 19(6), 1635-1650.
[16] Uzen, H., Turkoglu, M., & Hanbay, D. (2021). Texture defect classification with multiple pooling and filter ensemble based on deep neural network. Expert Systems with Applications, 175, 114838.
[17] Alsaffar, M. F., Haleem, Z., & Hussian, M. N. (2020). Study some immunological parameters for Salmonella Typhi patients in Hilla city. Drug Invention Today, 14(2).
[18] Gebejes, A., & Huertas, R. (2013). Texture characterization based on grey-level co-occurrence matrix. Databases, 9(10), 375-378.