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A Literature Review on Medical Images Texture Analysis

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***Abstract*—An effective method of enhancing the information available from medical photographs is the examination of textural properties. Research in this area is still being done, and applications range from the segmentation of certain anatomical features and the identification of lesions to the separation of diseased from healthy tissue in various organs. While using radiological pictures acquired during standard diagnostic procedures, texture analysis entails a variety of mathematical operations carried out using the images' data. In this article, we examine research of the approach and explain the fundamentals of texture analysis while providing instances of its applications.**

I. INTRODUCTION

Traditionally, medical imaging has been evaluated subjectively or visually, leaving most of the latent data contained in the pictures untouched. Utilising radiomics, which is the quantitative information extraction from clinical imaging, is one method of getting access to this concealed information. In particular, the visual evaluation of variability in images is inadequate. Poor patient outcomes and intratumoral heterogeneity are related to tumour aggressiveness. In studies evaluating the diagnosis, prognosis, and response to therapy of cancer, several radiomic measures, in particular texture analysis metrics, were reported to quantify intratumoral heterogeneity.

An examination of texture, shape, and size is a typical component of radiomic evaluation. The technique's fundamental presumption is that the tumor's phenotypic changes, which are suggestive of genetic as well as molecular differences, are reflected in the gray-scale values used to create the picture of the tumour and the geographic and temporal correlations between these values.

The look, structure, and arrangement of an object's pieces inside a picture are referred to as the texture of the image. Digital images are employed in clinical practise for diagnostic purposes. A two-dimensional digital image is made up of tiny rectangular blocks called pixels (picture elements), as well as a three-dimensional digital image is made up of tiny volumetric blocks called voxels (volume elements); each of these is represented by a set of spatial coordinates and has a value that denotes the intensity of that imagine or volume element in terms of its grey levels. We will limit the topic to pixels because most medical pictures are two-dimensional, but expanding it to voxels or volumetric imaging is simple. The arrangement of grey-level numbers among the pixels in a particular region that is important in a picture may be used to explain the texture notion in digital images.

Texture analysis is a key field of study for computers. Because of the richness of natural texture, it is a challenging challenge. Between nearby pixels, there had been a noticeable difference in colour or intensity levels. Techniques for texture analysis were used to categorise the photos or objects. The process of segmenting a texture into smaller parts was once used to analyse the borders of the texture. The texture is a component of the texture analysis that

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divides and categorises pictures into regions of interest. It generated a little pixel value, while the rough texture had huge values. The texture, which has homogeneity qualities and does not have a single colour or intensity, was used to refer to the visual pattern. One is feature extraction. Texture segmentation. Artificial intelligence is now widely employed in a variety of scientific sectors, including health, agriculture, construction, tourism, and biochemistry, thanks to advances in information technology and hardware. Image processing and computer vision comprise a significant portion of the applications throughout the several fields of artificial intelligence study [1]. All computer vision-based solutions are ultimately designed to execute tasks that the human eye can do more rapidly and correctly. According to recent studies, the human eye typically employs three elements—color, texture, and shape—to determine an image's kind.

However, texture is more significant [2]. In order to analyse and extract texture information from photos, a number of operators have thus far been introduced. The spatial pattern of the illumination intensity of each pixel, which is regularly repeated throughout the entire picture or specific regions of it, is referred to as an image's texture [3]. picture texture is the idea of how naturally an item appears in a picture. In actuality, everyday items have texture. Even people attempt to create things by repeating a texture. For instance, humans created the repeated texture on a brick wall. A tiger's bodily structure also has a texture and repeating pattern. Even a mobile device's screen or how the keyboard is shown has a particular design that gives a picture texture and enables humans to identify an object.

The initial stage of texture analysis is feature extraction, which determined the characteristics of pictures that characterise the texture attributes. The second stage of texture analysis has been completed using the feature extraction results. The texture segmentation process, which is the second step, separates the texture picture into parts with the same texture.

II. Literature Review

Displaying the digital data as a three-dimensional map based on the pixel values is one approach to represent this. Thus, in theory, texture analysis is a method for determining the location and strength of signal characteristics, or pixels, as well as their intensity at different grey levels, in digital pictures. Texture characteristics, which identify the kind of texture and subsequently the underlying structure of the objects presented in the image, are in reality mathematical parameters determined from the distribution of pixels. Structured, model-based, statistical, and transform approaches are the several types of texture analysis that are grouped together depending on how they analyse the connections between the pixels [1].

This uses precise primitives to express texture. In other words, the straight lines or primitives that make up a square object's boundary are used to represent it. These approaches have the benefit of offering a strong symbolic representation of the visual. However, it is better for an image's synthesis than for its analysis. For structural analysis, the theory of morphology in mathematics is an effective resource. Here, utilising complex mathematical models (such fractal or stochastic), an attempt is made to express texture in a picture. For the picture analysis, the model's parameters are calculated. The computational complexity required in these parameters' estimation is a drawback [2].

Many classification jobs in actual production environments encounter difficult obstacles including skewed category distributions and numerous performance metrics to satisfy. This study offers a solution to these issues and uses it to automatically classify surface flaws on display glass. The suggested approach is divided into two main steps: (1) utilising threshold-moving to handle class skewness and satisfy particular quality targets, and (2) using a straightforward ensemble to take into account numerous quality objectives in a problem with classification while keeping computing costs as low as possible. An industrial case study's findings show that the suggested method may effectively replace human examination of display glass. Future research might determine the ideal ensemble size and composition, explore the usage of more complex models, and investigate other ways to optimise the ensemble approach for better classification performance[3].

Using colposcopic images, Ji et al.12 employed texture analysis to describe and identify typical, diagnostically significant vascular patterns associated to cervical lesions. They developed a generalised texture analysis method that integrated structural textural analysis and traditional statistical methods to provide a set of texture measures that described the distinctive features of cervical textures as seen by medical exams. With the use of those measurements, they showed how well the suggested method distinguished between cervical texture patterns suggestive of various stages of cervical lesions. These are based on texture representations that make use of the arrangement and relationships of the image's grey level values. The discrimination indices that these approaches often attain are greater than those of the structural or transformation methods. Clinical practise can benefit greatly from the extensive texture information present in medical photographs. Current electromagnetic (MR) pictures of tissues, for instance, are unable to deliver microscopic data that may be evaluated visually. The texture of the MR image may, however, vary due to histological modifications prevalent in specific diseases, which may be quantified via texture analysis. The categorization of diseased tissues from the liver, thyroid, the breasts, kidneys, the prostate, heart, brain, and lung has effectively used this method[4].

Saeed and Puri used T1-weighted three-dimensional MRI of adult control and patients to analyse texture data in order to divide the cerebellum. Alejo et al.'s (17) partially automatic delineation of the hippocampus and the corpus callosum employed neighborhood evaluation of texture-based MRI data. Herlidou et al.18 compared roughness with visual analysis of MRI data for the identification of skeletal muscular degeneration in a previous research utilising texture analysis. They came to the conclusion that skin texture analysis can offer valuable information that can help with skeletal muscle illness identification[5].

In order to show a pathological condition with common manifestations that causes a change in the texture of the brain, Kovalev et al. used texture variables obtained from gradient vectors and from generalised co-occurrence matrices for the description of texture of some MR-T2 brain images. For separating the brain pictures of controls from those with white-matter encephalopathy and/or Alzheimer's disease, they employed extended multisort co-occurrence matrices, which uniformly incorporate intensity, gradient, and anisotropy image data. These textural traits were also used to segment diffuse brain lesions[6].

White matter, grey matter, cerebrospinal fluid, tumours, and edoema were all characterised using textural parameters depending on the histogram, co-occurrence matrix, gradient, and run-length matrix in Herlidou et al's study. In addition to confirming that MR pictures, including those produced during normal operations in three separate MRI units, include tissue-specific texture characteristics that can be retrieved by mathematical approaches, they were successful in differentiating the various brain tissues[7].

The cortical thickness & hyperintense T1 signal, as well as the blurring of the grey material/white matter interface, were determined using a combination of textural parameters by Bernasconi et al. and Antel et al. in a series of investigations using T1-weighted cerebral MR images. They were able to automatically identify certain localised cortical dysplasia lesions that the human eye would have missed. They claim that patients with serious seizures caused by focal cortical dysplasia may benefit from presurgical assessment using the new computer-based, automated technique[8].

To enhance the characterisation of brain tumours, Mahmoud et al. applied the texture analysis method based on a three-dimensional co-occurrence matrix. They conducted a comparison study to assess how well this method performed in comparison to the two-dimensional method, utilising T1-weighted MRI of 7 glioma patients to differentiate between solid tumour, necrosis, and the surrounding white matter. They were better able to distinguish between oedema and solid tumours as well as between necrosis and solid tumours using the three-dimensional technique. Neither of these techniques allowed them to completely distinguish ipsilateral white matter from ipsilateral white matter or peritumoral white tissue from oedema. They do, however, argue that the current three-dimensional technique may offer a novel tool for planning radiation or surgical therapy as well as for tumour classification and treatment follow-up [9].

In a research by Yu et al., individuals with unilateral temporal lobe epilepsy who had ipsilateral hippocampal sclerosis on MRI and a seemingly healthy contralateral hippocampus participated. They started by confirming that the normal (control) and sclerotic hippocampi had different textures. They then demonstrated how the texture of the contralateral hippocampi, which initially appeared to be normal, could be divided into three groups: seemingly healthy, comparable to sclerosis, or distinct from either healthy or sclerotic. They linked these results to a specific level of hippocampus change, which called for more research to provide a more accurate characterisation [10].

Using texture parameters determined by run-length and co-occurrence matrices, Bonilha et al.8 and Coelho et al.10 verified the findings. In a related work[11], Jafari- Khouzani et al. used wavelet-based texture characteristics to discriminate between abnormal and healthy hippocampus tissue in order to help doctors decide which patients might benefit from epilepsy surgery [12].

Mathias et al. attempted to assess the pathogenic changes that take place in multiple sclerosis (MS) by using texture data relating to MRI of the spinal cord. Before spinal cord degeneration could be seen visually, texture variations between healthy controls & relapsing-remitting MS patients were discovered. Additionally, they discovered a strong connection between textural alterations and impairment [13].

In order to characterise and identify typical, diagnostically significant vascular patterns associated with cervical lesions from colposcopic pictures, Ji et al. performed texture analysis. They developed a generalised texture analysis method that integrated structural textural analysis and traditional statistical methods to provide a set of texture measures that described the distinctive features of cervical textures as seen by medical exams. With the use of those measurements, they showed how well the suggested method distinguished between cervical texture patterns indicative of various stages of cervical lesions [14].

Chabat et al. employed 13 textural features to distinguish between various obstructive lung disorders in thin-section (CT) pictures. These factors were obtained from the histogram, co-occurrence matrix, and run length matrix categories. Patients with constrictive obliterative bronchiolitis, centrilobular emphysema, and healthy participants were all given a series of CT scans. They established the viability of textural differentiation between the lungs of healthy persons and those with illnesses that result in lower attenuation of the lung parenchyma. They came to the conclusion that the technique had a high degree of accuracy and recommended that it be used as one of the primary CT feature extractors for the automatic identification of obstructive lung disorders [15].
Uniform LBP was carried out in various radius sizes for the detection of breast cancer by Zeebaree et al. [16]. The overall structure of the suggested strategy in [16] is 6. As previously indicated, four alternative LBP histograms are built using different thresholds, such as the centre intensity, mean of neighbours, maximum intensity between neighbours, and lower value.
LBP and Curvelet transform were used by Bruno et al. [17] to classify breast cancer. The ultrasound breast picture is first converted to the curvelet domain. Then, LBP is used to modified pictures at various sizes. Finally, feature selection approach is applied to decrease complexity.
Arya et al.'s [18] use of a collection of textural features for the categorization of pap smear images. The two steps of the suggested method are feature extraction and classification. First, from the input single cell picture, common handmade texture characteristics including Law's, discrete wavelet transform (DWT), local binary patterns (LBP), and gray-level co-occurrence matrixes (GLCM) are retrieved. For the classification step, linear support vector machine (SVM) is utilised next.
Additional work of authors is summarized below:

Author	Title	Work	Methodology
E. S. Gemeay, F. A. Alenizi	Weighted Constraint Feature Selection of Local Descriptor for Texture Image Classification	Filter-based feature selection is the method for choosing features that are proposed. For each characteristic, it used a weighted constraint score. A threshold estimation approach is suggested to choose the most discriminating features after ranking the features. A variety of distinct datasets are utilised as a baseline to evaluate the comparative approaches for a more accurate comparison.	The suggested technique may produce excellent classification accuracy without a learning phase by using just a few descriptor features, according to implementations on the Outex, UIUC, CUReT, MeasTex, Brodatz, Virus, Coral Reef, and ORL face datasets.
Mahmoodian, H. Thadesar, M. Georgiades, M. Pech and C. Hoeschen	Liver Texture Classification on CT Images of Microwave Ablation Therapy	The knowledge of tissue characterisation for lowering the recurrence rate is improved by this research. In this case, the categorization of liver tissues was done using four machine learning (ML) algorithms: Naive Bayesian, Logistic Regression, Decision Tree, and Random Forest. In this study, we suggest bispectral analysis at higher orders for extracting features from CT images. Ten fresh features obtained from the bispectrum analysis were then used to train classifiers. Small sections of the photos were separated into healthy, tumorous, and ablated tissue categories in order to achieve this.	90.5% accuracy was the highest possible. The method demonstrates that, even in the presence of noise, the bispectral analysis gives useful information that may be employed during MWA therapy for tissue characterisation of CT scans.
Li and R. Mukundan	Robust Texture Features For Emphysema Classification In CT Images	Emphysema may be divided into three subtypes using a unique feature extraction technique that utilises local quinary patterns (LQP), multifractal features, and intensity histograms. In order to express texture characteristics, the LQP technique determines more image local patterns than local binary patterns. For this classification assignment, multifractal characteristics that improve local textures are merged with other features to form a feature vector. Prior to using an SVM classifier, the dimension of the feature vector is decreased using an autoencoder networks and principle components analysis. An emphysema database with 168 annotated areas of interest from three distinct subtypes is used to evaluate the suggested technique.	The experimental findings show that our methodology surpasses the majority of existing cutting-edge methods, with an excellent classification accuracy of 92.3% when utilising the feature vector with the fewest dimensions (15).
Omer, W. A. Abbas, M. ElHelw, G. S. Seifeldein	Combined regional and spatio-temporal approach improves hepatic tumors classification in Multiphase CT	Examine the impact of employing regional spatio-tepmoral characteristics on the ability to classify liver focal lesions in multiphase CT images. To more accurately characterise five hepatic diseases using multiphase contrast-enhanced CT images, texture, weight, and temporal feature sets as well as their various combinations along spatially partitioned ROI were studied.	A total of 180 ROI, including normal tissues, cysts, haemangiomas, metastatic cancer, and hepatocellular carcinoma, were classified using embedded feature selection, decision tree ensembles classification, and ten folds cross-validation. Our findings revealed that while texture characteristics could detect HCC with almost the greatest accuracy, density features alone could distinguish

			normal liver tissues with ease. Combining all of the features might get superior results consistently for all tumour kinds while overcoming individual performance discrepancies between them. Additionally, adding regional details enhances the classification of all groups, particularly haemangiomas and metastases.
Yu, C. Wang, S. Cheng and L. Guo	Establishment of Computer-Aided Diagnosis System for Liver Tumor CT Based on SVM	A computer-aided diagnostic (CAD) system that can identify hepatocellular carcinoma (HCC) areas and normal liver regions in liver tumour spectral computed tomography (CT) images to assist medical professionals in diagnosing and treating patients. The HCC and normal liver regions of interest (ROI) are each used to extract first-order statistical texture characteristics and gray-level co-occurrence matrix (GLCM) texture features, respectively. We employ a support vector machine (SVM)-based classification model, and we choose the optimum feature preprocessing technique and SVM parameter based on the experimental findings of various feature preprocessing techniques and kernel functions. In order to lower the dimensionality of the features, increase the classification model's learning speed, and produce the CAD system, we apply principal component analysis (PCA).	In the training set, the normal ROI's average classification accuracy is 92.22%, whereas the HCC ROI's average classification accuracy is 87.93%. In the testing set, the normal ROI's average classification accuracy is 90.62%, whereas the HCC ROI's average classification accuracy is 86.36%. Professional doctors have acknowledged the experimental findings.
A. Banday and A. H. Mir	Statistical textural feature and deformable model based MR brain tumor segmentation	For the aim of diagnosis and therapy planning, segmentation of anomalies is one of the key areas of concentration in the field of medical image processing. In the work presented in this paper, a semi-automatic method that produces suitable segmented areas from MR brain images has been suggested and put into practise.	The segmentation approach utilised in this instance creates a fused feature map by fusing information from MR images that is outside the range of human vision. Second order derivatives derived from an image are among the information that is outside the range of human vision and are covered in full in the relevant portion of this work. In the context of an active contour model, the resulting feature map serves as a stop function for the initialised curve to produce a precisely segmented region of concern. Using Jackard's Coefficient of Similarity and Gap index, the results of our segmentation approach are compared to the manual segmentation results of experts that serve as the basis for the comparison. The outcomes of several case studies, including those involving Craniophryngioma, High Grade Glioma, and Microadenoma, demonstrate the general method's high effectiveness.
K. Lau and M. Palaniswami	Automatic segmentation of the rima glottidis in 4D laryngeal CT scans in Parkinson's disease	The authors offer an automated segmentation approach that uses textural characteristics and support vector machines (SVM) to separate the rima glottidis from 4D CT images. The area is then precisely segmented as a post-processing phase using automatic two-dimensional region growth. We show a strong association between the manually segmented region and the suggested segmentation technique, which led to accurate segmentation.	When almost 70% of the dopaminergic neurons in the midbrain have perished, symptoms start to show. Vocal impairment may be detected by a temporal study of the rima glottidis area computed.
Mushtaq and A. H. Mir	Forgery detection using statistical features	Digital photographs are susceptible to a variety of forgeries, with copy-move and splice forgeries being the most popular. The innovative technique for detecting picture copy-move and splicing in this study is based on statistical characteristics of the digital image. To hide any crucial information, copy-move entails copying a part of an image then pasting it someplace else in the same picture. Splicing is combining two or more photos to create a composite picture that differs greatly from the original.	For both the faked pictures and the real images, the suggested method creates grey level run length matrix (GLRLM) texture characteristics. For classification, support vector machines are employed. Results demonstrate how well the suggested method detects forgeries.

III. CONCLUSION

Here, we've covered how to analyse textures in medical photos. Texture parameters are only mathematical illustrations of aspects of a picture that may be expressed verbally as smooth, rough, grainy, and so forth. This indicates that, in theory, texture evaluation may be used on any collection of picture areas that can be distinguished from one another using such a description. With the exception of Ji et al.'s work with colposcopic pictures and Chabat et al.'s work with CT, MRI uses have been highlighted when discussing the major categories of texture characteristics and the many applications of each technology.

Since texture analysis is a method developed to extract from medical pictures additional information that is difficult to convey by eye inspection, such analysis is still constrained by the low resolution of images, MRI applications predominate in the literature regarding this methodology. Therefore, it is an approach that has promise for future advancements in the calibre of medical pictures. The strategy, which may be used in a variety of image applications while taking into account the drawbacks of each imaging technology, is by no means restricted to MRI. In addition, the use of texture characteristics is not limited to the diseases covered in this article; rather, it is beneficial for the research of other pathological situations for which imaging is a suitable investigative technique.

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