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Review Article

Advances and Insights in Image Texture Analysis : A Review

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ABSTRACT

Texture analysis is an essential step in image analysis, and subsequent applications such as medical imaging, remote sensing, and scene understanding are highly important in image processing. Although it is vital, the field presents its own set of research challenges, especially when manipulating variations in texture patterns and requirements for properties that remain unaffected by related transformations, such as rotation, scaling, and translation. This review provides an in-depth description of key activities in the field of texture analysis, including classification, segmentation, synthesis, and image retrieval, along with their strengths and limitations. The approaches are classified as structural, statistical, and model-based and are discussed in consideration of their appropriateness and performance. The regular textures most favour structural methods, whereas statistical and model-based methods are more flexible, although they sometimes require more computational resources. Other challenges that are outlined in the review include a lack of support for real-time and transform-invariant applications. These findings can aid in determining the appropriate techniques to use and in developing lightweight yet durable methods for texture analysis. Overall, the review offers profound insights into the field and provides a course for future research and creativity.

1. INTRODUCTION

The texture, as a concept of both visual and tactile senses, is a critical parameter that significantly contributes to understanding the characteristics of surfaces and perceiving patterns in natural and constructed landscapes. Texture analysis is a vital technique in the fields of image processing and computer vision and is used in medical imaging, industrial object detection, and scene interpretation. Nevertheless, despite its significance, recognizing texture in real-life conditions is a complex task because of the need for proper and efficient recognition. Unlike human perception, which can perceive texture automatically, computational systems must contend with complex texture variation, which can be affected by aspects such as lighting conditions, scale, orientation, and sensor differences [1].

Texture analysis plays a pivotal role in various applications, including medical imaging, industrial object recognition, and pattern classification. However, real-world conditions such as changes in illumination, scale, and orientation complicate texture recognition, necessitating robust feature extraction techniques [2]. Traditional methods rely on hand-crafted features, whereas advanced approaches, such as Convolutional Neural Networks (CNNs), enable automated feature learning and uncover unique and latent texture characteristics for classification and retrieval tasks [3].

The core challenge lies in designing texture analysis techniques that remain effective across these variations. Traditional methods based on manual crafting features typically lack generalizability when presented with transformations, such as statistical or structural attributes. The alternative methods, model-based approaches with Convolutional Neural Networks (CNN) in particular, have resulted in automated feature interpretation and greater depth of texture knowledge. Nevertheless, these models require a significant amount of computation time and resources. Hence, they lack the necessary appropriateness in real-time or low-resource conditions. Therefore, critical evaluation and systematization of the whole variety of approaches to texture analysis are needed [4], [3].

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This review aims to fill this research gap by implementing a detailed assessment of texture analysis techniques, categorized into seven primary method groups: statistical, structural, transform dependent, model-based, graph-based, learning-based, and entropy-based methodologies. The primary objective will be to evaluate the applicability, strengths, and weaknesses of each type, with special attention to transformation-invariant methods, which can resist rotation, size, and position shifts. The techniques that strike a balance between accuracy and efficiency in computation are also highlighted in this paper, with consideration for the concerns of real-time analysis in real-life conditions.

Importantly, clarify that this review is limited to methods that are not specifically applicable to highly limited or highly specialized problems, such as highly regular or synthetically generated textures. Methods that have specialized properties for a wide range of texture types. The inclusion criteria focus on techniques that assist invariance to geometrical transformations, such as rotation, translation, and scaling, and may be applied to real-life situations where various lighting conditions, perspectives, and acquisition devices are involved. Computational efficiency and scalability are also essential criteria for inclusion, particularly in real-time applications or platforms where resources are limited. To maximize the coverage of texture feature representations, the review also includes a set of different descriptors highlighted in recent literature.

The rest of the paper is organized as follows: Section Two provides a brief introduction. Section three focuses on the challenges faced in texture analysis. Section Four explains texture analysis and its various categories. Section Five presents an overview of the datasets used in texture analysis. The limitations of current methods are discussed in Section Six. Section Seven focuses on the results, including a comparison of the most commonly used methods for texture analysis. Future directions are outlined in Section Eight. Finally, the conclusions are presented in Section Nine.

2. Application of Texture Analysis

Texture analysis has widespread applications in various fields, including engineering, medicine, biology, environmental science, and multimedia. Its ability to quantify surface patterns and spatial arrangements of pixel intensities makes it essential in interpreting visual data.

2.1 Medical application in texture analysis

Texture analysis has become one of the most effective approaches in medical imaging to provide potential information about tissue heterogeneity and to be helpful in several practical uses. In oncology, it has the potential to measure macroscopic tissue heterogeneity, which is related to macroscopic features beyond the scope of human visual perception [5]. These features assist in predicting treatment response and patient prognosis. However, despite promising results, widespread clinical adoption remains limited due to challenges such as poor model generalizability across imaging devices, lack of standardized protocols, and the need for explainable AI models in critical decision-making. Advanced approaches, such as CNN-based texture extraction, have demonstrated improved accuracy but demand large, annotated datasets, which are often unavailable in medical domains [6].

2.2 Texture in Remote Sensing

Remote sensing is a method of obtaining information about objects or areas from a distance via satellites, airplanes, or ground sensors to capture images of the Earth's surface. This technique is particularly beneficial for gathering information about specific areas that cannot be directly accessed or observed; it often yields complex images that display various features of the territory. Although these techniques provide a high level of recognition of patterns, they are highly susceptible to environmental factors such as changes in illumination, seasonal variations, or atmospheric interferences. Additionally, high-resolution data and transformation-invariant models pose persistent issues, particularly in the analysis of multi-temporal or multi-sensor data. [7].

In this way, through texture understanding, we can recognize and distinguish one area from another, for example, forests or cities, without labelling each image separately for recognition. Texture features are most useful in a variety of applications, including analysing changes in the surface, evaluating the use of land, and marking areas affected by disasters [8].

2.3 Texture Analysis of Satellite and Aerial Imagery

The term "texture" in satellite and aerial imaging pertains to the observable patterns and irregularities contained in the images, which depict various geographical surfaces. The analysis of texture plays a vital role in the identification and distinction of natural and man-made objects inside images, hence facilitating diverse applications in fields such as agriculture and forestry [9]. Alternatively, in the event of a forest fire, regions impacted by intense fire have a more uniform visual pattern. Nevertheless, a severe shortcoming that can occur is the inability to respond to the changing spatial resolution and variance of appearance due to atmospheric effects. Furthermore, existing algorithms do not always generalize to different geographic areas unless they are retrained, or the parameters are tuned [10].

2.4 Texture-Based Approaches in Scene Understanding

Texturing facilitates the understanding of continuous patterns, such as the wavy motion of water or the flickering of fire, which are crucial for distinguishing different scenes. For several years, researchers have attempted to connect static and dynamic textures, resulting in an expanded LBP methodology that extends from a two-dimensional plane to a three-dimensional volume and integrates motion and appearance data (features) to represent dynamic texture information.

Deep Belief Networks (DBNs) are a type of artificial intelligence that has been specifically designed to acquire knowledge from data in a manner similar to human learning. DBNs are particularly good at recognizing and classifying images and videos, such as different natural scenes, by learning from the textures and patterns they contain [11]. However, these models are very cost-demanding and, most of the time, operate as black boxes, a factor that limits transparency and confidence in sensitive operations. Moreover, the robust performance of a system across different lighting conditions and varying scenes with clutter remains an open research problem [12].

3. The Challenges

Textural analysis has faced several challenges due to the complexity and variability of textural patterns across various textural domains. The following can be put under these categories: feature representation, classification, segmentation, synthesis, data limitations, and model limitations:

3.1 Feature Representation Challenges

Textural images can be complex and diverse, making it challenging to define a universal set of features that can accurately represent all types of textures. In terms of texture, classification encounter challenges due to occlusion, variations in the focal point, distortion, changes in brightness, and interference from the background [13].

3.2 Texture Classification Challenges

In texture classification, occlusion, variations in focal length, geometric distortion, illumination changes, and background clutter often obscure texture patterns, making accurate categorization difficult. These factors result in intraclass variability and interclass similarity, complicating the classification process [10].

3.3 Texture Segmentation Challenges

In texture segmentation, the problem is compounded by high intra-phase homogeneity, particularly in material images, wherein pixels within the same phase exhibit substantial similarity, leading to difficulties in precisely distinguishing and segmenting different phases [11].

3.4 Texture Synthesis Challenges

Lastly, generating textures that go beyond those represented in the training data is a challenge in texture synthesis [14]. Additionally, seam and distortion problems in traditional methods can affect the quality of synthesized textures [15].

3.5 Data and computational limitations

High computational costs and long processing times are common, especially for deep learning models. In addition, the limited availability of labelled training data for texture analysis is considered the main factor that affects performance [15], [16], [17], [18].

3.6 Model limitations and open issues

One of the most dramatic trends can be seen in the use of deep learning and artificial intelligence in texture recognition. Provingly effective are convolutional neural networks (CNNs), Vision Transformers (ViTs), and wavelet scattering networks, as these models learn hierarchical features automatically with only the data to find the answer. Nevertheless, there are still open problems, such as [3], [19], [20]:

- Attaining strong domain shift robustness.
- Assuring the interpretability of the learned features.
- Similarly, designing generalizable models that work well with versatile datasets of textures.
- Dealing with the bias and equity in training data.

Fig. 1 shows a sample of texture analysis challenges. The top two rows show dramatic intraclass variations, whereas the bottom two rows show small intraclass variations, which makes the problem more difficult. The images in the third row are from the FMD database, and the images in the last row are from the LFMD database [21].

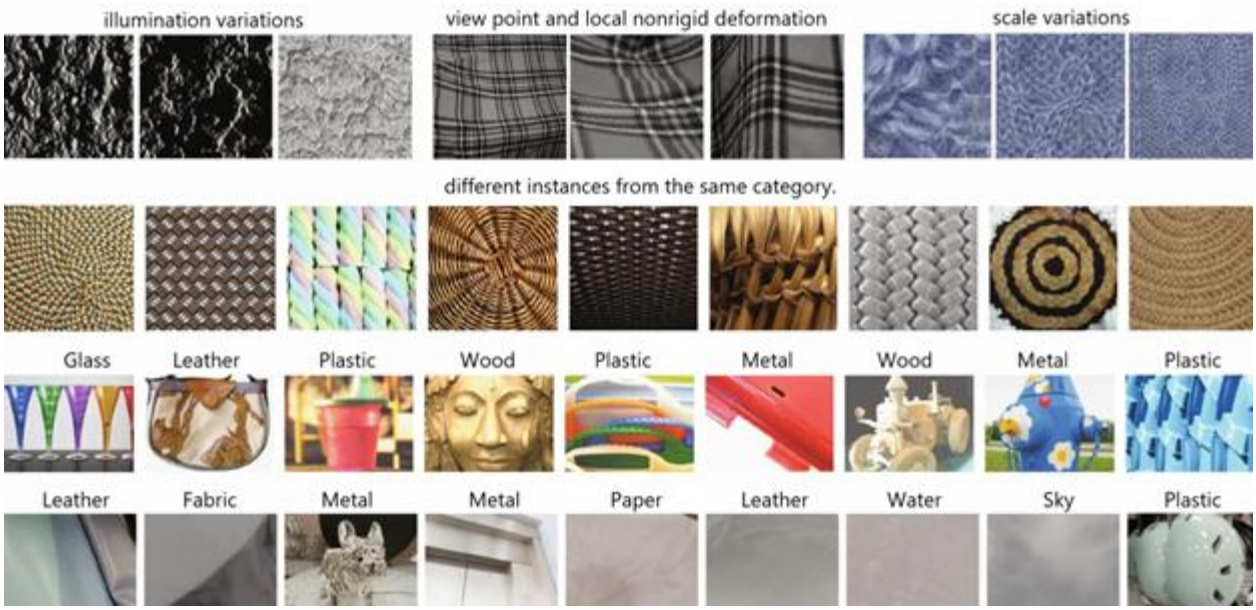

Fig. 1. Samples of texture analysis challenges [21].

To address these challenges, recent research has explored lightweight and efficient models capable of preserving the same performance but with reduced computational overhead. Additionally, self-supervised and semi-supervised learning algorithms that are used during training to address the lack of labelled data via unlabelled algorithms are actively designed [22]. Table 1 lists the challenging areas, key issues, and suggestions to solve these issues.

TABLE I. TEXTURE CLASSIFICATION CHALLENGES, AND PROPOSED SOLUTIONS

Challenge Area	Key Issues	Proposed Solutions
Feature Representation	No universal features for all textures	Learn hierarchical representations via deep networks
Classification	Occlusion, lighting, distortion, background clutter	Data augmentation, robust feature learning, attention mechanisms
Segmentation	High intraphase similarity in material images	Deep learning-based segmentation with texture priors
Synthesis	Limited generalization, seam artifacts, distortions	Generative models (GANs), improved loss functions, patch-based synthesis
Data Limitations	Lack of labelled data	Semi/self-supervised learning, synthetic data generation
Computational Cost	High runtime and resource demand	Lightweight models (e.g., MobileNet, EfficientNet), quantization
Model Limitations	Domain shift, interpretability, poor generalization, dataset bias	Domain adaptation, explainable AI, fairness-aware training

4. Texture analysis

The core of texture analysis is computing texture features. In recent years, researchers have proposed many theories and algorithms. However, we can trace the history of texture analysis back to 1962.

In the early 1980s, the development of classic texture analysis methods was strongly influenced by texton theory. In the late 1980s and early 1990s, texture analysis research focused mainly on spectral methods (such as Fourier transform and wavelet transform) and model-based methods (such as Markov random fields and fractal models). Promising local texture descriptors such as local binary patterns appeared in the early 2000s [23].

Using the bag-of-textons and the bag-of-words in 2001 represents the starting point for the transition phase from handcrafted to learned methods. Since 2012, deep learning techniques have received increasing attention from researchers and have been applied to texture analysis. Milestones in texture representation over the past decades are listed in Fig. 2.

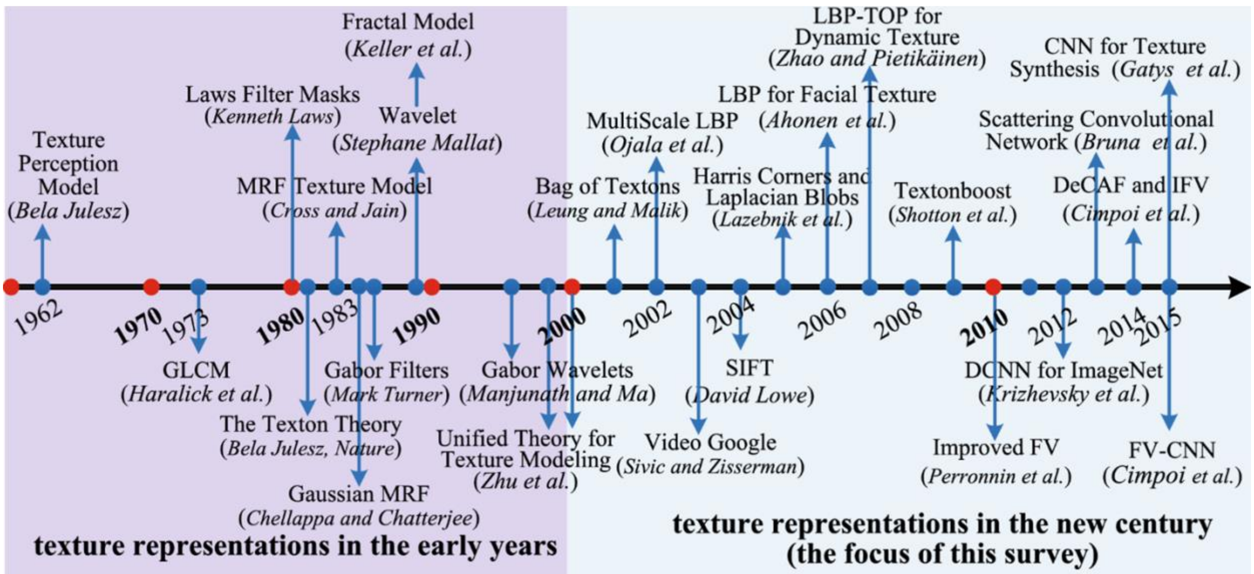

Fig. 2. Evolution of texture representation over the past several decades [21].

Methods for analysing texture are very diverse and differ from each other, Texture analysis can be divided into four main areas, as shown in Fig. 3.

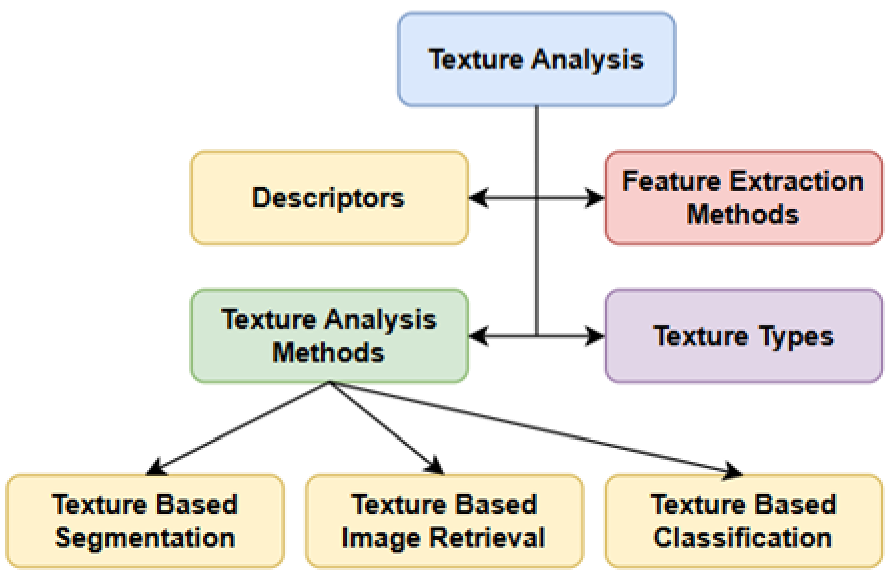

Fig. 3. Classification of Texture Analysis Methods [by Authors].

4.1 Texture Types

Understanding various texture characteristics and properties is useful for analysing patterns and structures in images. According to these characteristics, textures are grouped into many types. The texture types are illustrated in the block diagram shown in Fig. 4. A sample of various textures is shown in Fig. 5.

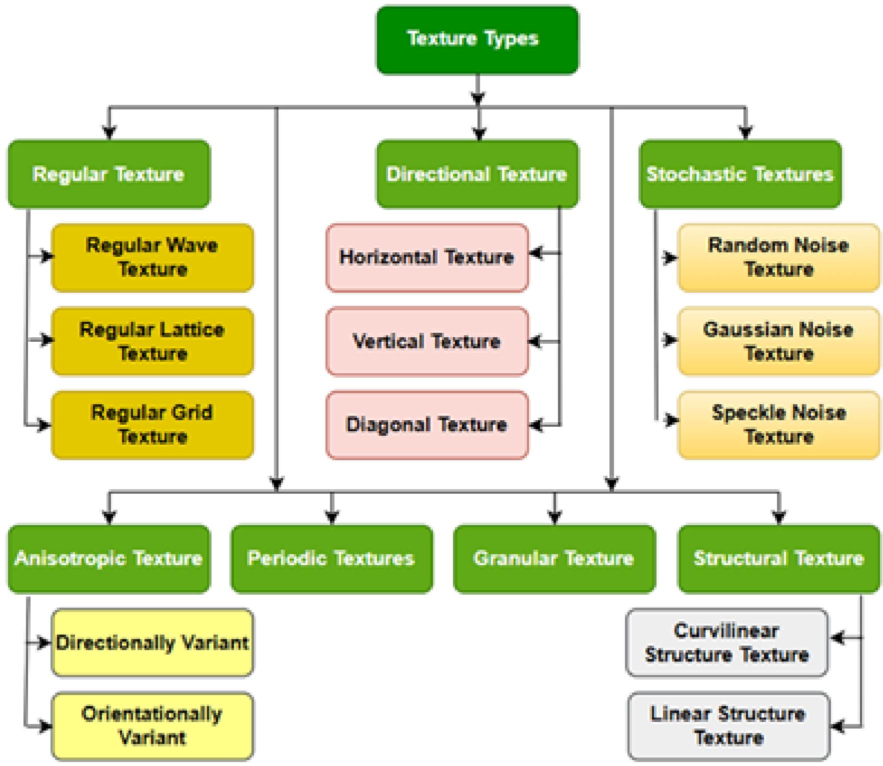

Fig. 4. Block diagram describing texture types [by Authors].

A. Regular Texture:

This refers to repeating patterns periodically, such as tile flooring, which is characterized by consistent geographic repetition [24].

- **Regular Grid Texture**: Two-dimensional periodic textures with micropatterns set in a geometrical grid, such as checkerboards and window grilles [25].
- **Regular Lattice Texture:** Highly regular textures with repeating units defined by size, color, shape, and orientation, creating a strong perception of order [26].
- **Regular Wave Texture:** Wave-like surface patterns are used in applications such as marine rainfall detection by analysing wave differences in radar texture maps [27].

B. Stochastic Textures:

Lack of regularity, showing randomness in patterns [28].

- **Random Noise Texture:** Simulates natural, non-repetitive variations for realistic surfaces in digital environments such as fires or clouds [29].
- **Gaussian Noise Texture:** Textures generated with Gaussian noise, following a bell-shaped distribution, are commonly used in stationary Gaussian models [30].
- **Speckles Noise Texture:** Found in ultrasound and sensor imaging, this noise is caused by light wave interference and poses challenges for meaningful data extraction [31].

C. Structural Texture:

It is composed of sub patterns with features such as symmetry, brightness, and size [32].

- **Linear Structure Texture:** Patterns formed by one-dimensional lines in varying orientations, generated via algorithms such as Bresenham's [33].
- **Curvilinear Structure Texture:** Patterns with curved shapes, which are common in medical imaging (e.g., blood vessels), are analysed by orientation and ripples [34].

D. Directional Texture:

Refers to texture's perceived directionality, aiding in classification and pattern recognition [35], [36].

- **Horizontal Texture:** Dominant alignment along the horizontal axis.
- **Vertical Texture:** Dominant alignment along the vertical axis.
- **Diagonal Texture:** Alignment along diagonal axes, adding dynamism.

E. Anisotropic Texture:

Material properties vary with orientation and are often linked to crystallographic or structural alignment [37].

- **Directionally Variant:** Varies with stress or force applied in different directions [38].
- **Orientationally Variants:** Relates to internal structure behavior, such as crystallographic alignment [39].

F. Granular Texture:

On the basis of particle size and distribution, these materials are categorized as fine-grained or coarse-grained materials [40].

G. Periodic Textures:

Repeating patterns or motifs found in both natural and artificial contexts, such as QR codes [41].

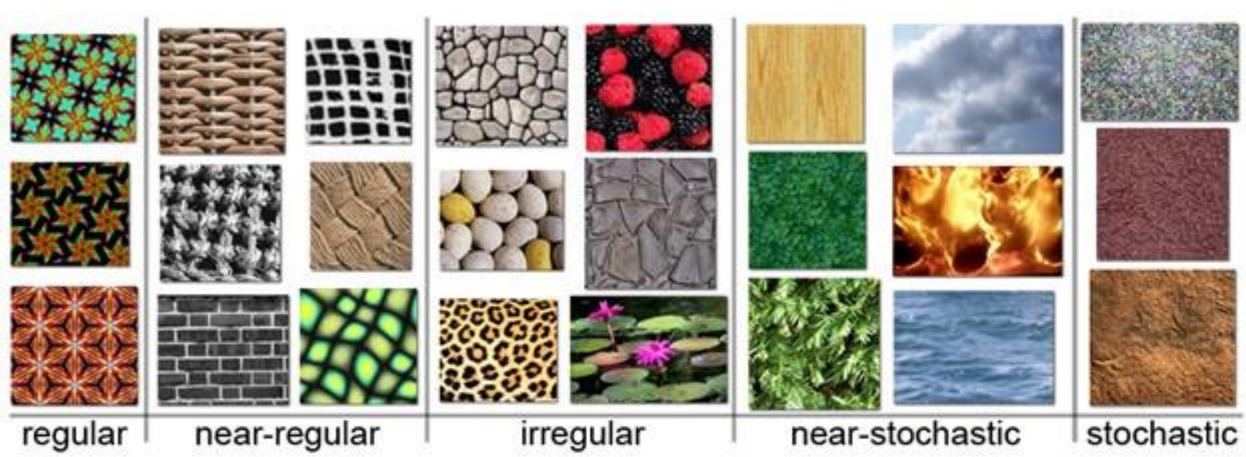

Fig. 5. Samples of texture types [42].

4.2 Texture analysis methods

Texture features are informative for object detection, surface defect detection, and medical image analysis. Texture analysis methods involve classification, segmentation, and image retrieval. Each task has a special purpose in analysing and processing texture information. Over the past few decades, many approaches have been developed to increase the efficiency of these tasks. The following sections describe each of these tasks [43].

4.2.1 Texture-based classification methods

Texture classification can be broadly categorized into three main approaches. Each approach offers unique techniques for analysing and distinguishing texture patterns, contributing to diverse applications in computer vision and image analysis. Fig. 6 shows the main and subcategories of texture-based classification.

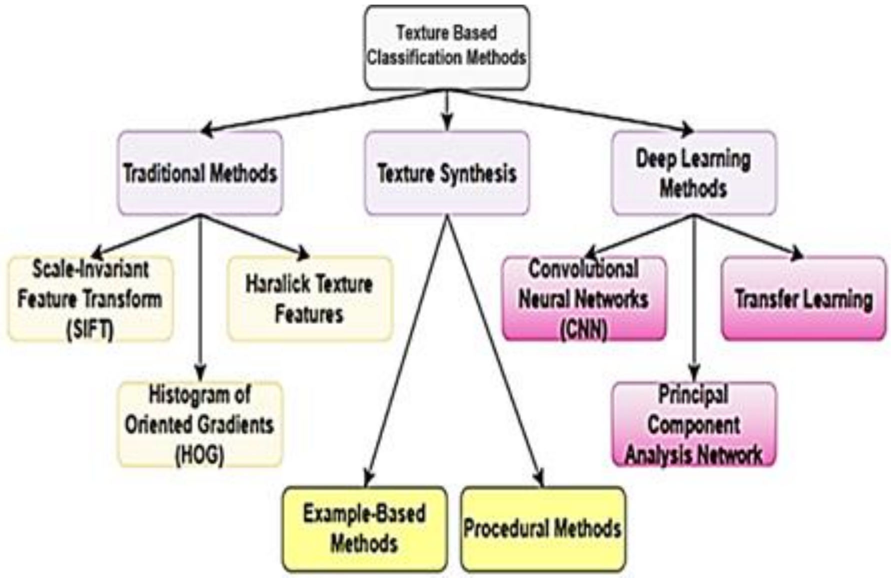

Fig. 6. Block diagram for texture-based classification methods [by Authors].

4.2.1.1 Traditional Texture Analysis Methods

Traditional methods are foundational approaches in texture analysis that focus on handcrafted feature extraction. They are computationally efficient and remain relevant in scenarios with limited data or computational resources. A recent study has shown that traditional texture descriptors, such as Local Binary Pattern LBP, can surpass CNNs in certain situations. These findings demonstrate that these descriptors might be valuable depending on the specific application [44].

A. Haralick features

Derived from the Grey-Level Co-Occurrence Matrix (GLCM), these features quantify spatial relationships between pixel intensities, capturing texture properties such as contrast, entropy, and homogeneity. Haralick features are widely used in medical imaging, remote sensing, and material science for texture classification and segmentation, as they effectively encode spatial dependencies in textures [45].

B. Scale-Invariant Feature Transform (SIFT)

As a robust method that extracts invariant features under rotation and scaling, SIFT is widely used for object recognition and texture matching across varying perspectives. SIFT is robust against scaling, rotation, and noise and is effective for object recognition, scene matching, and 3D reconstruction[46]. SIFT is widely used in computer vision tasks such as image stitching, object recognition, and motion tracking [47].

C. Histogram of Oriented Gradients (HOG)

This method partitions images into cells, calculates the gradient orientations, and compiles them into histograms, effectively encoding local texture and shape information for applications such as object recognition. HOG captures fine-grained edge and texture information and is robust to slight variations in appearance, pose, and lighting. Due to its ability to represent object shapes and textures effectively, HOG is extensively used for object detection (e.g., pedestrian detection) and image classification [48].

4.2.1.2 Deep Learning Texture Classification

Deep learning approaches, particularly **Convolutional Neural Networks (CNNs)**, are widely used for texture classification. CNNs are trained on large datasets of labelled texture images to learn discriminative features and patterns. Once trained, the model can classify new texture images on the basis of their visual characteristics. Compared with traditional methods, deep learning excels in texture classification because of its ability to capture complex and hierarchical representations of textures [49].

A. Convolutional Neural Networks (CNNs)

CNNs are foundational deep learning architectures for image-related tasks. They consist of [50]:

- **Feature extraction layers**: Convolutional, nonlinear, and pooling layers that identify patterns.

- **Classification layers:** Fully connected layers that map extracted features to output categories. CNNs have been instrumental in achieving state-of-the-art results in many vision tasks, including texture classification.

B. Principal Component Analysis Network (PCANet)

PCANet combines **Principal Component Analysis (PCA)** for dimensionality reduction with CNNs for feature extraction. It is simple to implement and effective for specific tasks, such as facial recognition and digit classification. However, it may not perform well on tasks requiring more advanced feature extraction [51].

C. Transfer Learning

Transfer learning leverages pretrained CNN models, such as those trained on ImageNet, for texture classification tasks. By adapting these models to new datasets, transfer learning reduces training time and improves performance while requiring less data. Fine-tuning the pretrained model ensures optimal results for the specific task [52].

4.2.1.3 Texture Synthesis

Texture synthesis involves generating new textures that closely resemble a given set of input textures by analysing their features and replicating their characteristics. The techniques for texture synthesis are broadly classified into procedural methods and example-based methods [14].

A. Procedural methods

Procedural methods create textures via mathematical models, often employing parameters, noise functions, or existing textures as inputs[53]. These methods are advantageous for generating textures of unlimited size and resolution. However, these methods pose challenges in predicting outcomes, as small changes in parameters can drastically alter texture appearance [54].

B. Example-based methods

Example-based methods generate textures by using preexisting samples and statistical models. Techniques **such as patch-based synthesis** and **Markov Random Field (MRF) synthesis** are commonly employed [55]. These methods allow flexibility in output control and produce textures that are visually similar to the original samples. However, they depend heavily on the quality and diversity of the input examples, are computationally intensive, and may struggle to preserve intricate details and high-frequency features in the synthesized textures [56].

4.2.2 Image Segmentation

Image segmentation divides an image into parts for more straightforward analysis, which is crucial for fields such as medical imaging, object detection, and agriculture. Texture segmentation, a subset of image segmentation, is categorized as follows [57]:

Texture-based segmentation plays a crucial role in texture analysis by leveraging surface pattern variations to divide an image into meaningful regions. Common approaches include three methods, as shown in Fig. 7, each employing texture features to achieve accurate and efficient segmentation.

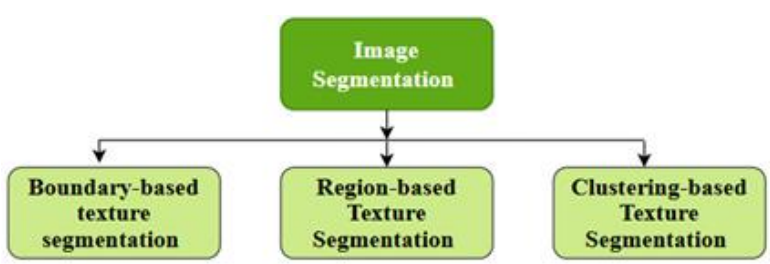

Fig. 7. Image segmentation methods [by Authors].

A. Region-based segmentation:

Group pixels with similar textures. This method is suitable for classifying regions on the basis of texture. This method is useful in medicine and astronomy but can face over segmentation and high computational demands [58],[59].

B. Boundary-based segmentation:
This method focuses on defining texture boundaries and is effective for detailed texture analysis. High accuracy is offered but can be affected by noise and gaps [60].

C. Clustering-Based Segmentation:
Combines feature extraction and clustering for texture-based segmentation. It is effective but computationally intensive and requires optimal parameters [61].

4.2.3 Image Retrieval Based on Texture

Image retrieval is a critical application of texture analysis, leveraging extracted texture features to search for and retrieve visually similar images from large databases. Image analysis examines the visual elements of images, such as textures, shapes, or colors, to identify the ones most comparable to the desired search results. This procedure is frequently employed in diverse domains, such as digital repositories, medical imaging, and e-commerce, wherever users desire the identification of images that exhibit visual similarities to a given sample image or correspond to a specific description [62].

4.3 Descriptors

Metrics are used to quantify and describe texture features in images. They capture spatial properties such as coarseness, smoothness, and regularity, providing a means to analyse the arrangement of pixels within a region or the entire image [63]. Based on the calculation method, descriptors can be categorized into three main types, as shown in Fig. 8.

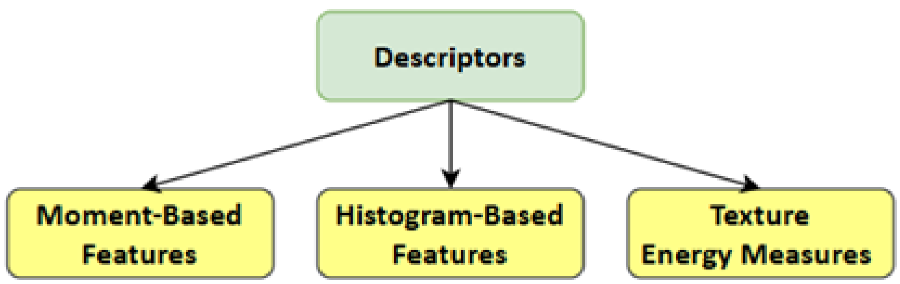

Fig. 8. Categories of Descriptors [by Authors].

A. Moment-based features
These features mathematically represent the shape and structural characteristics of objects in images, making them valuable for tasks such as optical character recognition (OCR). Despite their utility, moment-based features can be computationally intensive and sensitive to noise [64].

B. Histogram-Based Features
These features summarize image data in histogram form, a common approach used for feature extraction, enhancement, and classification in applications such as artistic image processing and medical image classification. While robust, they may lack the ability to capture complex patterns, often necessitating complementary techniques [43][65]. Standard histogram-based features include contrast, which measures the intensity variation between a pixel and its neighbor across the image and aids in distinguishing different regions [4]. Correlation, which evaluates the linear relationship between neighboring pixels, is valuable for texture classification[66]. The angular second moment (ASM), also known as energy, quantifies texture uniformity, with higher values indicating more consistent textures, and the inverse difference moment (IDM), which reflects local homogeneity and is useful for detecting smooth and uniform textures [67], [66], [68].

C. Texture Energy Measures (TEM)
TEMs analyse and characterize image texture by applying filters or masks to extract features such as patterns or statistical properties. They are effective for identifying repetitive or random structures in textures. Examples include the Laws of Texture Energy Measures. However, processing high-resolution images or large datasets can be computationally demanding, leading to the development of optical implementations to improve efficiency [69].

4.4 Texture feature extraction

One of the most essential research directions in image processing, computer vision, and remote sensing is the extraction of texture features. Recently, texture feature extraction approaches have been categorized into seven main categories, and some of these categories can be further divided into several subcategories, as shown in Fig. 9.

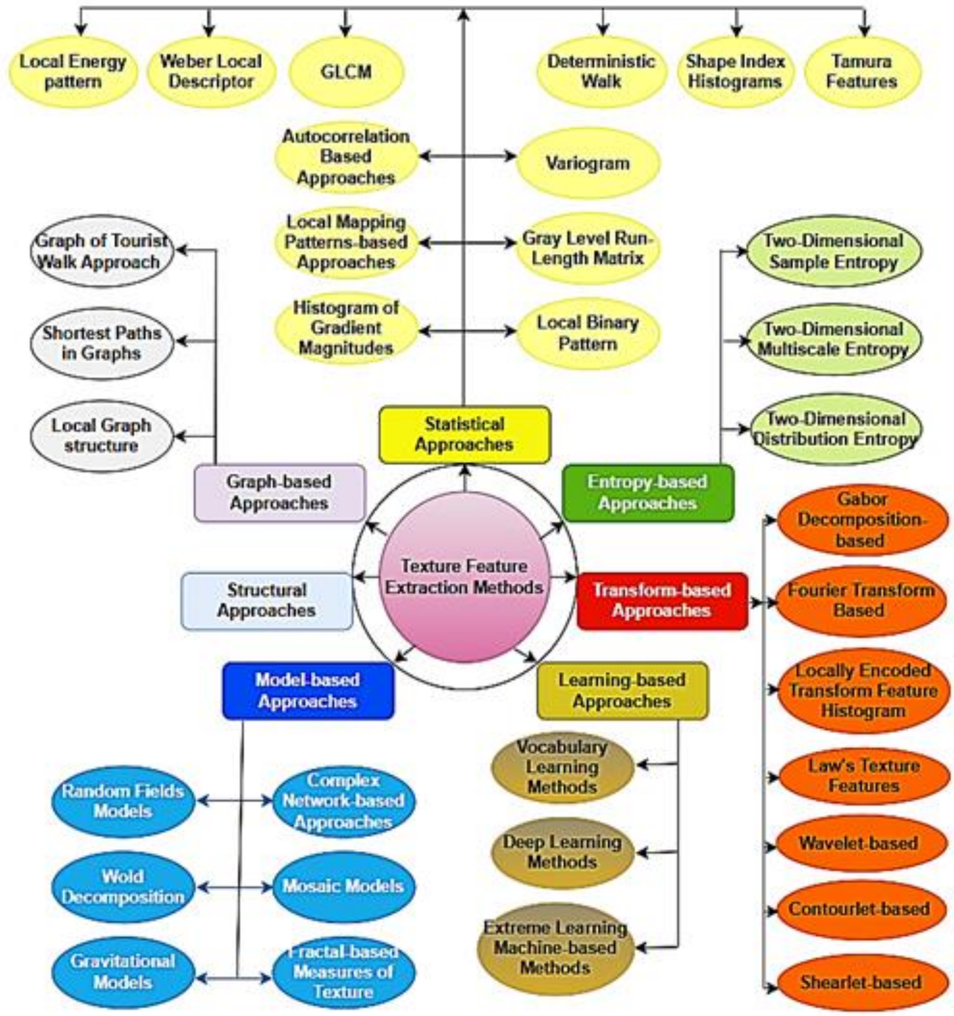

Fig. 9. Block diagram for texture feature extraction methods [by Authors].

4.4.1 Statistical Texture Analysis

A quantitative approach for analysing the spatial distribution of pixel intensities is used to extract meaningful texture information [70].

A. Local Binary Patterns (LBP)

- An efficient method for texture extraction was proposed by Ojala *et al*. [71].
- Each pixel is labelled by comparing it with its 3×3 neighbors, and a histogram of 256 bins is created [72].
- Limitations: Affected by rotation and using random binary weights [73].

B. Grey-Level Co-occurrence Matrix (GLCM) [74], [75]

- Textures are analysed by calculating the probability density of pixel pairs with specific values and spatial relationships.
- This method is useful for distinguishing textures but depends heavily on selected parameters (distance and angle).

- Limitations: Computationally expensive for large datasets.

C. Grey Level Run-Length Matrix (GLRLM)

GLRLM quantifies textures by analysing the distribution of pixel runs with the same grey level in specific directions (horizontal, vertical, and diagonal). Coarse textures exhibit longer runs, whereas fine textures have shorter runs. Features such as short-run emphasis, long-run emphasis, and run uniformity describe texture patterns. While the GLRLM has applications in medical imaging and material classification, studies suggest that its efficiency is lower than that of other methods. Improvements include advanced algorithms such as fuzzy local binary patterns. Applications span biomedical differentiation and industrial texture recognition [76]

D. Autocorrelation-based approach

Autocorrelation measures periodic patterns in an image by calculating the dot product of the image with shifted copies. It helps detect coarseness and sub-pattern directionality. Larger primitives lead to slower decay in autocorrelation, whereas smaller ones decay rapidly. The method generates a "rose of directions" to capture texture orientations. Although useful for texture inspection in some applications, such as visual inspection and seabed segmentation, it struggles with distinguishing coarseness and isotropy in natural textures [77].

E. Histogram of Gradient Magnitudes

The histogram of gradient magnitudes, proposed by Sharma and Ghosh in 2015, computes the strength of image edges by evaluating the magnitude of gradients without considering their orientation, making it rotation invariant. This method is effective in texture recognition and classification. It outperforms descriptors such as LBP [77].

F. Local Energy Pattern (LEP)

Zhang *et al*. (2013) suggested a texture classification approach that uses local feature vectors on the basis of the energies of image regions. The oriented energies are computed by processing the image with Gaussian-like filters, which are summed and normalized. This method represents the global texture by generating a histogram. The advantages of LEP are its invariance to imaging conditions and reduced quantization loss, which makes it an effective method for applications related to texture [78].

G. Variogram

In this method, the spatial image texture is analysed by calculating the difference between pixel values at a particular distance. The variogram is characterized by its computing simplicity, but it is sensitive to outliers [79].

H. Tamura features

The Tamura features are a set of six texture descriptors developed to correspond to human visual perception. These features include coarseness, contrast, directionality, line-likeness, regularity, and roughness, which are particularly effective for texture classification and segmentation. The key advantage is that they are visually meaningful and are based on psychophysical principles. However, they may not always perform well in all contexts compared with other methods. Applications include historical document analysis, biomedical image retrieval, and texture description in linguistic terms [76].

I. Shape index histograms

The shape index histogram method, proposed by Larsen *et al*. in 2014, uses the shape index, a geometric measure that captures second-order image structure. This method generates histograms of curvature distributions and employs a rotation-invariant spatial pooling scheme. It is particularly effective for blob-like structures. The approach is intuitive, but the number of bins is determined ad hoc. Applications include classifying indirect immunofluorescence images of HEp-2 cells into different staining patterns [23].

J. Weber Local Descriptor (WLD)

The Weber Local Descriptor (WLD) is based on Weber's law and incorporates two components: differential excitation and gradient orientation. Differential excitation measures the relative intensity difference between the current pixel and its neighbors, whereas the orientation component captures the gradient direction. The WLD descriptor is used for texture classification by constructing a 2D histogram of the feature values. A multiscale version, known as Counting and Difference Representation (CDR), improves discrimination. WLD has applications in gender recognition from facial images [23].

K. Deterministic Walk method

The deterministic walk method, introduced by Backes *et al*. in 2010, uses a "tourist" to explore an image on the basis of a deterministic rule. The tourist visits neighboring pixels on the basis of geometric distance and intensity differences, following a set walking rule. The method captures the transient time and cycle period joint probability distributions, and the histogram quantifies texture behaviors. Textures with regular patterns exhibit peaks, whereas those with irregular patterns show more uniform histograms. This method explores textures across all scales simultaneously and has applications in wear particle identification [76].

4.4.2 Structural Approaches

Focus on decomposing textures into basic elements or primitives, such as uniform grey levels, line segments, or edge separations, which are arranged in a regular pattern. These approaches aim to identify texture primitives and their spatial relationships via methods such as boundary detection and Fourier analysis. These methods are particularly suitable for regular textures but are not ideal for highly random textures. Structural methods are effective for symbolic image descriptions and are used in applications such as nuclear chromatin characterization in Pap smears, where blob-like primitives are analysed [23]. A sample of the structural texture is shown in Fig. 10.

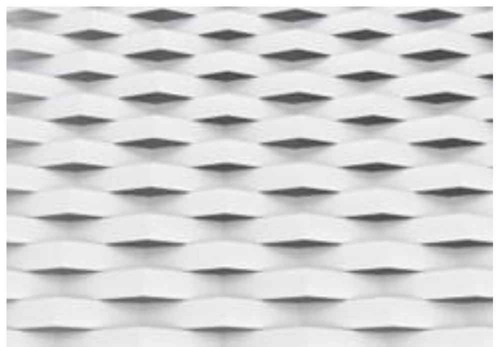

Fig. 10. structural texture image.

4.4.3 Transform-Based

Focuses on the spatial distribution of feature points in recurring textures, offering precise descriptions compared with those of statistical methods [80].

A. Gabor filters [81]**:**
- Directional textural features are extracted by capturing spatial and frequency information.
- Drawbacks: Computationally expensive, sensitive to noise, and limited to linear features.

B. Wavelet Transform [82]**:**
- Textures are analysed by decomposing images into frequency bands via the Discrete Wavelet Transform (DWT).
- This method is critical for applications such as image segmentation and remote sensing.
- Limitations: Require careful selection of wavelet functions and threshold values.

C. Fourier Descriptors (FDs) [83]**:**
- Features are extracted by breaking down images on the basis of partial derivatives and frequency information.
- Advantages: Invariant-to-geometric transformations and robustness to noise.
- Limitations: Poor spatial localization and challenges with textures having localized features.

D. Law's texture feature extraction:
Simple 1D arrays such as Level, Edge, Spot, Wave, and Ripple arrays are applied to create 2D masks for convolving digital images, emphasizing microstructures. Energy and other macrolevel statistical features are computed over large windows to characterize textures. While Law's measures lack rotational invariance, advanced methods such as Mellor’s introduce rotation and scale invariance by computing eigenvalues and eigenvectors from polar-separable filters. Applications include analysing soil textures, biomedical imaging, and identifying fibrotic regions via ultrasound with minimal user interaction [84].

E. Shearlet-based Approaches
He *et al*. (2013) developed a new approach for texture representation based on shearlet decomposition, local energy feature extraction, rotation-invariant encoding, and histogram concatenation. The shearlet transform provides an efficient way to describe textures with rotation invariance and noise robustness. It is a robust method and adaptable to different tasks [85].

F. Contourlet-based Approaches

Zhang *et al*. (2015) developed a robust framework (contourlet transform) to extract important texture features from elastography images. This approach extracts textures via contourlet decomposition, sub-band reconstruction, feature derivation, and averaging. It is beneficial for medical image applications[86].

G. Locally Encoded Transform Feature Histogram (LETRIST)

The LETRIST method, introduced by Song *et al*. in 2018, is a training-free approach for texture feature extraction. It computes extremum responses of Gaussian derivative filters at multiple scales and applies linear/nonlinear operations to extract discriminative texture features. These features are quantized into texture codes through thresholding and encoded across scales to construct feature histograms, which are concatenated to form the image descriptor. LETRIST is robust to noise, rotation, illumination, scale, and viewpoint variations and has applications such as facial recognition [87].

4.4.4 Model-Based Texture Analysis

Model-based approaches aim at representing texture via mathematical models (such as fractal or stochastic models). This technique represents textures via stochastic and generative image models, enabling accurate synthesis and analysis of diverse textures. The model parameters serve as a feature set for texture classification and segmentation [88].

A. Complex Network-Based Approach

This method models an image as a complex network where the pixels are nodes, and the edges represent their similarities. Weight matrices and thresholds define the network structure and extract features such as degree histograms and spatial patterns. This method achieves high classification accuracy and rotation invariance but has high computational complexity and sensitivity to noise, and parameter selection is challenging [89].

B. Mosaic models

Generative techniques for texture representation are based on geometric processes. They describe patterns by simulating the processes that could create them. Cell structure models divide the plane into random geometric "cells" with assigned colors or properties, whereas coverage models involve randomly placing shapes ("bombs") to generate textures. These models offer flexibility for matching diverse features but depend heavily on randomness. Applications include analysing real images to uncover structural insights and texture properties [90].

C. Random Field Models

There are four subcategories of Random Field Models. These models are used in texture analysis and synthesis, each focusing on different ways to model spatial relationships and dependencies between image pixels.

- **Autoregressive Models:** Pixels are weighted sums of neighbors. This method is simple and efficient for texture discrimination [91].
- **Moving average models:** Convolve the input process with a geometric transform that is adaptable to various textures [92].
- **Markov Random Fields:** Pixel intensity depends on neighbors. This method is used for image classification but is computationally intensive[93].
- **Generalized long correlation models:** Model long-range correlations with few parameters that are suitable for natural textures [94].

D. Fractal-based Texture

Analysis leverages self-similar patterns that repeat at multiple scales, with the fractal dimension quantifying the roughness of textures. This method is efficient but may not distinguish all textures, prompting the use of lacunarity to measure gap distributions. Fractal analysis has applications in medical imaging, such as breast tumor classification in ultrasound images [95].

E. Gravitational models

Texture analysis involves simulating a "gravitational collapse process," where pixels in the image are attracted to the center, resulting in distinct texture patterns. This model uses the Bouligand–Minkowski fractal dimension and lacunarity methods for feature extraction. Although it offers promising results, it has higher computational costs than do methods such as Gabor filters. Applications include plant classification and leaf identification [96].

F. Wold Decomposition

The textures are divided into three components—randomness, directionality, and periodicity. It is useful for modelling various textures, but estimating coefficients can be challenging. Applications include texture segmentation and remote sensing edge detection [97].

4.4.5 Graph-based Approaches

The methods of this class are those where the extraction of the texture features relies on graphs obtained from the input image.

A. Local Graph Structures
The texture is analysed by representing the image as a graph where each pixel and its (6) neighbors form the vertices. The neighbors' relationships are evaluated, assigning binary values on the basis of their relative grey levels. The extended version includes both vertical and horizontal graphs for broader spatial information, with two descriptors concatenated into a global feature. This method is fast, insensitive to illumination, and invariant to scaling and shifting. Applications include facial recognition and clothing classification [98].

B. Graph of the Tourist Walk Approach
Trajectories from tourist walks are used to construct a graph that represents pixel connections. These connections are analysed for their statistical position and dispersion, which serve as texture descriptors. This method is robust for micro-texture recognition, especially for rotated and noisy images. It has been applied to plant leaf texture analysis and froth image feature extraction [99].

C. The Shortest Paths
This method uses graph theory to analyse texture by treating the image as a landscape. The image pixels are represented as graph vertices, and Dijkstra's algorithm computes the shortest path between regions. This method's strength is its ability to capture both macro and micro-textures [100].

4.4.6 Learning-Based Approach

Recently, texture feature extraction based on learning has proven to be efficient in various applications, drawing more attention.

A. Extreme learning machines (ELM)
It is effective in applications based on texture classification, known as fast computation, and strong generalization [101].

B. Vocabulary learning methods
It is characterized by its flexibility and ability to adapt to various datasets, but one of its limitations is the need for complex computations [102].

C. Deep learning
CNNs have a good ability to learn automatically, and they are widely used in many applications. CNN has good performance in texture analysis and extraction. The limitations of CNNs are that they are computationally expensive and require large datasets [103].

4.4.7 Entropy-based methods

Recently, entropy-based methods have been extended to analyse image texture and are no longer limited to processing time series data. Entropy measures the irregularity and complexity of intermediate matrices. These methods provide promising results, and they are simple to implement [104].

A. Two-dimensional sample entropy (SampEn2D)
This method determines the degree of pixel pattern disorder by comparing square windows within an image. It is an automated method and rotation invariance, but the drawback of this method is that it is computationally expensive, slow, susceptible to parameter choices, and faces the problem of providing results with a smaller texture [105].

B. Two-dimensional distribution entropy (DistEn2D)
The limitations of SampEn2D have been addressed by this method. Therefore, the current method is characterized by rotation invariance, is less sensitive to parameter choices, is faster than SampEn2D, and yields results from smaller textures. This method creates template matrices after image normalization and then determines the distance matrix. The entropy is calculated by estimating the empirical probability distribution of the distance values [106].

C. Two-dimensional multiscale entropy (MSE2D)
This method extends SampEn2D based on the analysis of spatial scales. It uses various scales to create coarse-grained images and determine SampEn2D for each image. MSE2D is fast, but for large scales, undefined entropy values may be produced [107].

5. Datasets used in the texture analysis

Through decades of development in texture analysis, several datasets have been collected and used to test and evaluate texture descriptors in texture analysis techniques; these datasets contain realistic image transformations, including rotation, viewpoint, scale, and illumination alterations. Fig. 11 shows the most well-known datasets utilized for different texture analysis approaches [108], [109], [110].

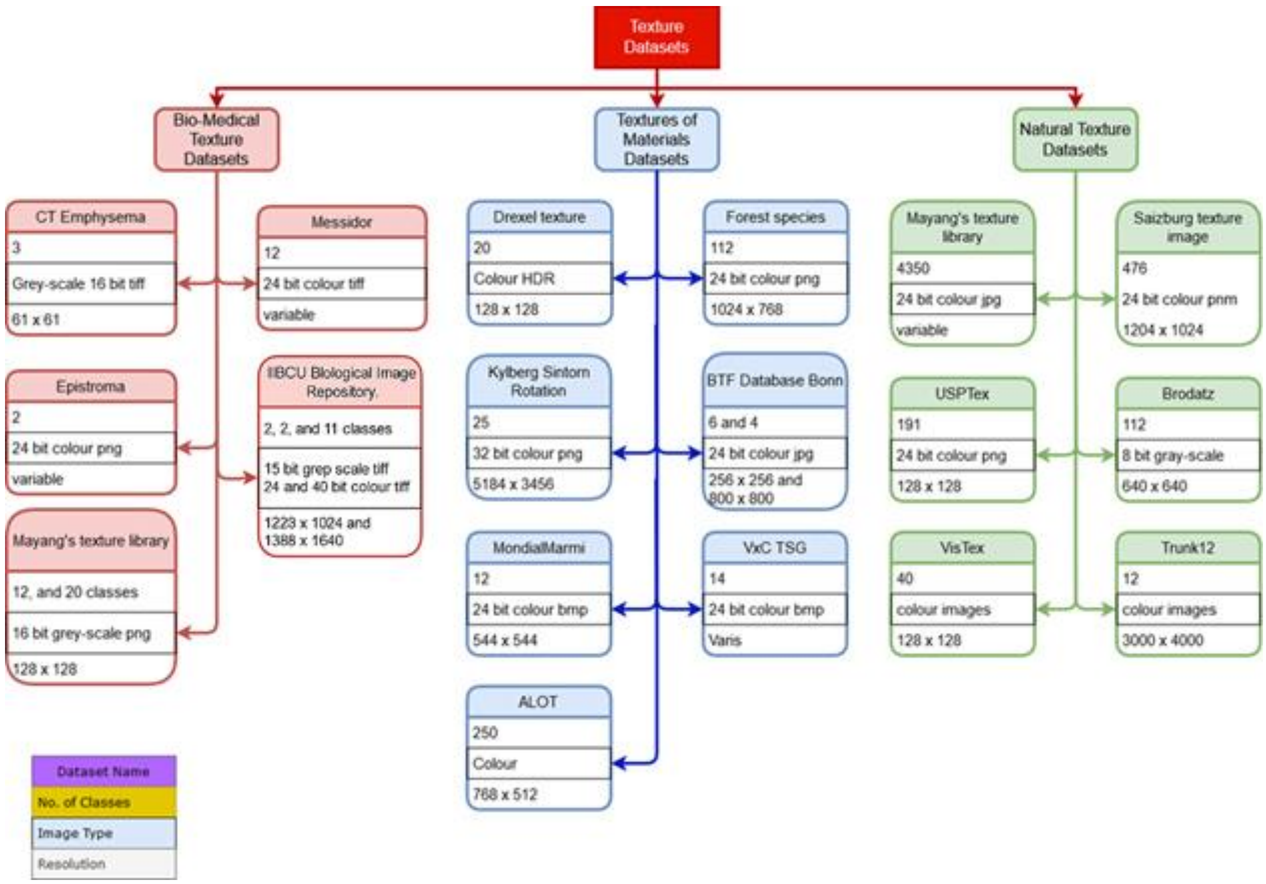

Fig. 11. Various databases used in texture extraction [by Authors].

Texture datasets with different applications exist. According to the nature of the data and the domain to which they belong, Table 2 presents a classification of widely used texture datasets categorized into bio-Medical, materials, and natural texture types.

5.1 Biomedical Texture Datasets

These are both greyscale and color medical imaging acquired single-modality images. These methods are mainly used in the detection of diseases and the analysis of biological tissues. Common sample datasets include CT Emphysema [111], Messidor [112], Mammographic Patches [113], [114], Epistroma [115] and the IICBU Biological Image Repository [116]. The datasets offer texture patterns derived from clinical imaging data that include CT scans, mammograms and histopathological slides.

5.2 Datasets Textures of Materials

These datasets contain the surface appearance of many physical materials with different illuminations, viewpoints or imaging conditions. Typical examples include the Drexel texture dataset [117], Forest Species database [118], Bidirectional Texture Function (BTF) Bonn [119], Kylberg rotation dataset [120], Mondial Marmi [121], VxC TSG (VxC Tiles for Surface Grading) [122] and ALOT (Amsterdam Library of Textures) dataset [123]. These data are necessary in applications of material recognition and reflectance modelling.

5.3 Natural Texture Datasets:

These collections of data are gathered from actual scenes and real-life scenarios. They are normally applied in the classification, segmentation and retrieval of images. Well-known libraries include the texture libraries Mayang [124], Brodatz [125], VisTex (Vision Texture) [126], Salzburg Texture (Stex) [127], University of São Paulo Texture dataset (USPTex) [128] and Tree Bark Image Dataset (Trunk12) [129]. These datasets differ widely in the number of classes, number of types of images, and image resolutions, so they are appropriate for many research situations involving texture analysis.

TABLE II. CHARACTERISTICS OF THE MOST COMMON TEXTURE DATASETS

No.	Dataset	Classes	Format	Resolution	Category	Notes
1	CT Emphysema	3	16-bit greyscale TIFF	61×61	Bio-Medical	Lung tissue analysis
2	Messidor	12	24-bit color TIFF	Variable	Bio-Medical	Fundus images for diabetic retinopathy
3	Epistroma	2	24-bit color PNG	Variable	Bio-Medical	Histopathological textures
4	Mammographic Patches	12, 20	16-bit greyscale PNG	128×128	Bio-Medical	Breast cancer screening
5	IICBU Repository	2–11	Mixed	Up to 1388×1040	Bio-Medical	Biological image textures
6	Drexel Texture	20	HDR color	128×128	Materials	Controlled lighting & surfaces
7	Forest Species	112	24-bit color PNG	1024×768	Materials	Wood and bark texture
8	Kylberg	25	32-bit color PNG	5184×3456	Materials	Rotation-variant analysis
9	BTF Bonn	6, 4	24-bit color JPG	Up to 800×800	Materials	Bidirectional texture functions
10	Mondial Marmi	12	24-bit BMP	544×544	Materials	Marble textures
11	VxC TSG	14	24-bit BMP	Varies	Materials	Surface granularity
12	ALOT	250	Color	768×512	Materials	Large-scale real textures
13	Mayang's Texture Library	4350	24-bit color JPG	Variable	Natural	Diverse outdoor scenes
14	Salzburg Texture	476	24-bit color PNM	1204×1024	Natural	Outdoor & object textures
15	USPTex	191	24-bit color PNG	128×128	Natural	Real-world texture variety
16	VisTex	40	Color	128×128	Natural	MIT's texture database
17	Brodatz	112	8-bit greyscale	640×640	Natural	Classical benchmark
18	Trunk12	12	Color	3000×4000	Natural	Tree bark classification

6. Current Limitations

Despite the significant successes achieved, several major limitations exist in the deployment of texture classification methods in practical situations. Their key weakness is that they are dependent on visual imagery taken in controlled settings. Indicatively, descriptors that work well on datasets such as Brodatz or VisTex tend to yield relatively lower accuracy when used on natural images such as forest bark textures or medically related images with image acquisition noise, such as those in the Trunk12 and Epistroma datasets [130], [131], [132].

In practice, the lack of clarity due to intraclass variability (e.g., various manifestations of a given disease in different patients) and interclass similarity (e.g., visually similar types of tumors) exist in the context of medical imaging, particularly remote sensing. It has been empirically proven that handcrafted descriptors such as Local Binary Patterns (LBP) drastically decrease in classification ability when domain-shifted or when presented with different imaging modalities [1], [133].

Additionally, vocabularies that are poor in spatial coverage are likely to lack a global context, which is important in any application, such as scene understanding or surface grading, as demonstrated by comparative analysis of the ALOT and VxC TSG datasets [134], [76]. Sensitivity to noise is another problem, especially in biomedical texts recorded with older or low-resolution equipment.

Recently, modern techniques have integrated classic descriptors with deep learning concepts in an attempt to enhance their generalizability and robustness. Nonetheless, scalability is still a problem because the required computational resources and large amounts of labelled data may not always be available in areas such as histopathology or satellite image processing.

7. RESULTS AND ANALYSIS

Table 3 summarizes the approaches used in recent studies, including their advantages and disadvantages, accuracy, and dataset.

TABLE III. A COMPARISON STUDY OF STATE-OF-THE-ART TEXTURE ANALYSIS METHODS

No.	Author	Paper title	Dataset	classifier	accuracy
1	Lukas Schepp [135].	Texture Classification Using ResNet and EfficientNet	Kylberg	ResNet V2	99.78%
				EfficientNet B4	92.97%
		Advantages	ResNet and EfficientNet, leveraging existing knowledge, save time and resources during the training process.		
		Disadvantages	vanishing gradients and overfitting in very deep networks, computationally expensive training		
2	Goyal V, Sharma S [136].	Texture classification for visual data using transfer learning	Brodatz	MobileNetV3	99.83%
			Kylberg		100%.
			Outex-v12		99.48%
			Brodatz	InceptionV3	99.94%
			Kylberg		99.89%.
			Outex-v12		99.48%
		Advantages	leverages existing neural network architectures, which can save time and computational resources		
		Disadvantages	transfer learning sometimes leads to overfitting if the new dataset is too small		
3	Lacombe T, Favreliere H, Pillet M. [137].	Modal features for image texture classification	Vistex	Full scale DMD with SVM	87.5%
			DTD		90.5%
			SIPI		95%
			Outex-V00		84.6%
			Outex-V13		72.5%
			SIPI Rotated		77%
			Vistex	Filtering DMD With SVM	95.4%
			DTD		95.2%
			SIPI		99.1%
			Outex-V00		75.4%
			Outex-V13		75.4%
			SIPI Rotated		/
		Advantages	DMD features are faster to extract, tested with rotated		
		Disadvantages	Does not tested with illumination changes		
4	el khadiri, I., Chahi, A., el merabet, Y., Ruichek, Y., & Touahni, R. [138]	Local directional ternary pattern A New texture descriptor for texture classification	Bonn BTF	KNN	99.88%
			Brodatz		100%
			Jerry Wu		98.23%
			KTH-TIPS		100%
			KTH-TIPS2b		97.47%
			Outex-1		99.15%
			Outex-13		80.32%
			VisTex		75.82%
			CUReT		91.54%
		Advantages	The method is robust against noise and illumination variations.		
		Disadvantages	Selecting optimal parameters for different datasets can be challenging.		
5	Sugiarto, B., Sari, C. A., & Arief Soeleman, M. [139]	KNN Algorithm Optimization in GLCM-Based Beef and Pork Image Classification	Beef and Pork	KNN	91.66%
		Advantages	effective in analysing textures and is invariant to rotation and exposure		
		Disadvantages	GLCM can only be used for greyscale images		
6	Armi, L., Abbasi, E. & Zarepour-Ahmadabadi, J. [140]	Texture image classification using improved local quinary patterns and a mixture of ELM-based experts	Brodatz	MEETG	96.38%
			ULUC		99.08%
			KTH-TIPS		95.97%
			Outex-12		89.90%
			ALOT		91.30%
		Advantages	combines the speed of Extreme Learning Machines (ELM) with a mixture of experts		

		Disadvantages	generally, ensemble methods are complex to implement, may require more computational resources and data		
7	Aggarwal, A., & Kumar, M. [141]	Image surface texture analysis and classification using deep learning	Kylberg	CNN	Model 1 92.42%
					Model 2 96.36%
		Advantages	Model-1 indicates a high level of accuracy when trained on a bigger dataset.		
			Model 2 indicates superior performance with a smaller number of training images.		
		Disadvantages	Model-1 There is some overfitting observed, may not perform as well on new, unobserved data		
			Model-2 Rapid variations in validation accuracy during training point to possible learning instability.		
8	Wang, J., Fan, Y., Li, Z., & Lei, T. [142]	Texture classification using multi-resolution global and local Gabor features in pyramid space	CUReT	nearest subspace classifier (NSC)	99.60%
			KTH-TIPS		99.36
		Advantages	global and local Gabor features, effectively capturing broad and detailed texture information		
		Disadvantages	The method may have moderate computational complexity, which could be a concern for real-time applications.		
9	Kas, M., khadiri, I. el, el merabet, Y., Ruichek, Y., & Messoussi, R. [143]	Multi-Level Directional Cross Binary Patterns The new handcrafted descriptor for SVM-based texture classification	2D-HeLa	SVM	71.58%
			Bonn BTF		100%
			Brodatz		100%
			CUReT		97.88%
			Jerry Wu		100%
			KTH-TIPS		100%
			KTH-TIPS2b		90.32%
			Kylberg		99.96%
			MondialMarmi		95.29%
			OuTeX-v0		99.97%
			OuTeX-v1		99.73%
			OuTeX-v13		88.7%
			UIUCTex		81.22%
			Vistex		85.05%
			XU HR		96.59%
		Advantages	Tested on multiple datasets, short time to analyse an image		
		Disadvantages	LBP-like descriptors still have significant drawbacks related to their susceptibility to noise and their ability to capture contrast information.		
10	Alpaslan, N., & Hanbay, K. [144]	Multi-Resolution Intrinsic Texture Geometry-Based Local Binary Pattern for Texture Classification	CUReT	KNN	96.9%
			USPTex		98.9%
			KTH-TIPS2b		97.9%
			MondialMarmi		100%
			OuTeX -13		94.5%
			XU HR		98.8%
			ALOT		97.20%
			STex		92.60%
		Advantages	captures textural changes efficiently, providing a more detailed and intrinsic understanding of texture.		
		Disadvantages	The method might have a higher computational cost due to the multiscale Hessian matrix calculation and the cross-scale joint coding strategy,		

The reviewed literature in Table 3 demonstrates a variety of approaches, which include classical handcrafted descriptors and recently developed deep learning architectures. In the following, we generalize the main findings of the comparative study along a variety of dimensions:

A. Classifier Trends

- **Models (deep learning) - CNN-based**: Researchers [135], [136], [141] have shown that architectures using convolution, such as ResNet, EfficientNet, MobileNetV3, and InceptionV3, have achieved state-of-the-art performance. According to research, the values for the Kylberg, Brodatz, and Outex data are consistently higher than 99%. Transfer learning has become an advantageous technique for reducing the shortage of large training datasets.

- **KNN and SVM (Traditional Classifiers):** Regularly applied alongside handcrafted features [137], [138], [139], [143], [144]. The classifiers are nevertheless robust benchmarks due to their low complexity and exemplary performance in well-separated features. Compared with KNN, the SVM scheme appears to be a superior generalization system for heterogeneous data.

B. Techniques of feature extraction

- **Handcrafted Descriptors:** The Local Directional Ternary Pattern (LDTP), Local Quinary Patterns (LQP), and GLCM have been proven to be very effective, especially in controlled conditions. They are subject to low computational complexity and easy to understand but can perform poorly when rotation, illumination, and noise are present, such as in [138], [139], [143].
- **Hybrid Models:** Other methods, such as DMD with SVM [137] and ELM-based expert systems [140] , are both highly efficient and accurate. Such techniques offer a trade-off between model complexity and generalization, but they require better tuning of the design and, in some cases, higher computational expense.

C. Generalization and use of the dataset

- **Frequently used datasets:** Kylberg, Brodatz, CUReT and Outex have been shown to be used in more than one study, and it has been concluded that they are popular among benchmarks. Strong accuracy can frequently be achieved with Kylberg and Brodatz methods (over 99%), indicating that simpler or appropriate features have been crafted.
- **Challenging Datasets:** DTD, SIPI Rotated, and Outex-V13 perform modestly in all the methods because of the relatively high possibilities of intraclass variation, rotation, or illumination issues. These datasets have shortcomings in terms of the robustness of descriptors [137], [143].
- Multi dataset evaluation. For papers such as [138], [143] and [144] It may be noted that due to the extensive spread of tests across various datasets, a more complex generalization evaluation is needed.

D. Accuracy distribution

- **Top Performers:** The transfer learning model by Goyal & Sharma with MobileNetV3 and InceptionV3 [136] records close-to-perfect results in all the datasets (as high as 100%). The LDTP approach by El Khadiri *et al*. [138] also achieves 100% accuracy on several datasets and is impervious to noise and variations in illumination. The trend continues with results greater than 95% likely to be achieved by the multilevel directional cross binary pattern of Kas *et al*. [143], again proving that handcrafted descriptors are not a dead end given the clever design.
- **Moderate Performers:** A relatively lower accuracy is displayed in models described by Aggarwal & Kumar [141] and DMD-based methods [137], which provides insight into learning how to utilize different dataset sizes and modal features.

8. Future Directions

Recent developments in texture analysis have increasingly focused on entropy and deep learning, both of which have shown great promise in many areas, such as classification, segmentation, synthesis, and retrieval. Despite these important improvements, there are still open challenges and possibilities for further research:

A. Development of Deep Learning Texture Analysis

Various deep learning models, especially convolutional neural networks (CNNs), vision transformers (ViTs), and hybrid models, have impressive capabilities in learning complex and hierarchical texture features. Nevertheless, their potential is not fully used because there are a few limitations:

- **Expensive computation and memory inputs:** Deep models that demand high-performance GPUs and large amounts of time during training, which constrain their application to real-time settings and resource-limited applications (e.g., robotics, Internet of Things (IoT), mobile vision systems), are common.
- **Minimal interpretability:** This is opposed to handcrafted features, as deep models can typically be perceived as black boxes, where the process of decision-making is complex to understand, and once again, this is vital in applications that are sensitive in nature, such as medical imaging.
- **Generalization gaps:** The models trained on a particular dataset are poor when they are introduced to variations in texture in the real world, e.g., occlusion, rotation, and lighting variations.

Future research should focus on the following:

- Architecture design of lightweight (e.g., MobileNet, GhostNet, and TinyViT) networks to achieve high inference efficiency without compromising the accuracy of performance. Pruning/quantization (or neural architecture search (NAS)) can be used to do this.
- Relying on explainable artificial intelligence (XAI) approaches to increase interpretation of texture analysis actions. Unsupervised and self-supervised learning can be used to better generalize unlabelled texture data.
- Exploring domain adaptation and few-shot learning to help models adapt to new or underrepresented texture classes with little data.

B. Enhancing Entropy-Based Texture Measures

The complexity, randomness, and structure of textures are described in terms of entropy-based descriptors. All these techniques are computationally inexpensive and tend to be resistant to noise. However, their practice continues to develop further, and there are still numerous gaps:

- Sensitivity to parameter tuning and scale selection.
- Limited integration with learning-based frameworks reduces adaptability across various domains.
- Scalability issues when applied to high-dimensional or large-scale texture datasets.

Future work could explore the following:

- Creating adaptive measures of entropy that itself optimize to a particular texture type or data scale.
- Using entropy features in combination with deep learning (e.g., failure is entropy-augmented CNNs or hybrid fusion approaches) to use both statistical strength and learned representations.
- The use of entropy measures as a regularization in neural networks to enhance the diversity of texture as well as in model generalization.
- Integrating entropy analysis into multiresolution frameworks potentially enhances feature stability across scale and rotation variations.

9. Conclusions

This paper aims to enrich the reader's knowledge of texture analysis by exploring the issues that arise from adapting to fundamental world aspects, particularly in circumstances where conditions demand invariance of transformation and require the program to be efficient. Unlike application-specific approaches, this review emphasizes general-purpose techniques, as they promote flexible approaches that can be applied to various domains without being limited to a single application.

The primary advantage of this review is that it focuses on general-purpose approaches rather than task-specific approaches, allowing the review to be applied to a wide range of application fields. The results highlight that there is no one-fits-all approach and that the preference should strongly rely on the nature of the texture, imaging acquisition, and invariance required thereof.

This Review covers existing problems, such as the trade-off between interpretability and adaptability, as well as the restrictions imposed by the complexity of computation in real-world settings. Such observations suggest that future works should be conducted towards the realization of lightweight, scalable yet interpretable models, particularly where they are needed to run models in strict resource budget conditions, such as in robotics and mobile systems.

Conclusively, this review, in addition to serving as a reference for current methods, can also provide insights into ways to further develop the robustness and general applicability of texture analysis in both research and practice.

Conflicts Of Interest

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