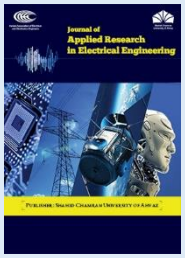
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Research Article

Texture Classification Using Deep Learning and Enhanced Local Binary Pattern

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Abstract: Image texture classification is crucial in machine vision and image processing. The primary step in this classification process involves extracting features from the image. Numerous techniques have been developed for feature extraction from textured images; however, local binary patterns (LBP), in both their original and enhanced forms, stand out due to their simplicity in implementation and their ability to extract effective features that yield high classification accuracy. Experts widely recognize that deep neural networks excel at classifying images and extracting detailed features. Building on the strengths of these methods, this study introduces a new model that merges deep learning with enhanced local binary patterns. This model has been tested on the Outex and CUReT datasets. The experimental results indicate that combining deep learning with an improved local binary pattern method significantly enhances the accuracy of texture image classification. According to these results, the classification accuracy of this new model surpasses that of previous methods.

Keywords: Classification, Deep learning, Texture images, Local binary pattern, Enhanced local binary pattern.

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1. INTRODUCTION

Texture classification is a crucial component of texture analysis, aimed at categorizing an unknown sample image into one of several predefined texture classes. Natural images often display variations in scale, illumination, viewpoint, and rotation, prompting texture classification methods to cover a broader spectrum of natural texture attributes. As a result, many approaches have been developed, falling into four primary categories: statistical, structural, model-based, and signal processing. Each category employs different techniques to extract features from texture images, tailored to the method used and the specific textures being analyzed. This research introduces a new model for texture image classification that integrates deep learning with an enhanced version of the local binary pattern (LBP). There have been numerous advancements in LBP methods, with some focusing on extracting distinct texture features through various pattern samples, and others enhancing noise resistance with different encoding or threshold strategies. This paper concentrates on the former approach, aiming to achieve high accuracy by extracting effective texture features and merging them with deep neural networks. Computer vision, a broad field of study, involves extracting and interpreting information from images and videos through computational algorithms. It addresses multiple challenges such as detection, segmentation, motion estimation, and image retrieval. Technological advances and the availability of extensive datasets have broadened its application scope. This paper specifically explores the combination of enhanced local binary patterns and deep learning methods for detecting and segmenting texture images. The goal is to extract relevant features from texture images and integrate them with convolutional neural networks (CNNs) for optimal texture

classification. The subsequent sections will discuss the refined versions of LBP methods tailored for texture classification, highlighting the unique challenges associated with handling texture databases. Here we delve into the literature review in this topic:

CNN, has become a dominant approach in texture analysis, object detection, and pattern recognition. [1] explored deep learning techniques for texture and dynamic texture analysis, demonstrating their effectiveness in capturing complex patterns in image data. Similarly, [2] investigated CNNs for object detection, re-identification, and recognition, highlighting their robustness in handling large-scale visual datasets. In real-world applications, CNNs have been employed for road defect detection, as seen in [3], where a CNN-based system was designed to detect potholes, improving road safety assessments. Another critical application is surface crack detection, where [4] proposed a shallow CNN architecture to enhance computational efficiency while maintaining high accuracy. Traditional texture descriptors, such as Local Binary Patterns (LBP), have been widely used in texture classification. [5] conducted a comparative study between LBP and deep texture descriptors, revealing that deep learning methods often outperform traditional approaches in robustness. Further improvements to LBP were introduced by [6], who proposed a completed modeling approach for better texture classification. [7] extended this idea with the Completed Local Binary Count (CLBC), enhancing rotation-invariant texture analysis. Peng Yang and colleagues have developed a descriptor that they use jointly for these challenges. They apply a complex Dual-tree Complex Wavelet Transform (DTCWT) to the base image to create an image pyramid. This pyramid is then merged with the Local Binary Pattern (LBP) in the DTCWT domain to formulate a method known as LBPDTCWT (Local Binary Pattern Dual-tree Complex Wavelet Transform), which is capable of generating robust texture features. By combining these features, their method has shown potential to surpass other approaches in empirical tests on benchmark datasets [8]. Tang Song and team introduced a fixed-scale descriptor called Sorted Local Gradient Pattern (SLGP) for classifying textures. Initially, they developed two complementary local gradient patterns, LGP Center (LGP CR) and Ring-to-Ring (LGP RR), to capture the rich gradient information in an image. Experiments on three texture databases indicate that this descriptor achieves superior classification results under affine transformations and both linear and nonlinear grayscale variations [9]. Creating effective features is a fundamental task in computer vision, yet finding a balance between discriminative power and robustness is challenging. Jianbai Yu and associates introduced a method named PRICoLBP, which shows resilience against changes in rotation and illumination. Previous methods have shown that enhancing spatial uniformity can improve the discriminative power of features. Despite their efficacy, existing uniformity-based features often overlook robustness against geometric and photometric variations. To address this gap, Jianbai Yu and colleagues explored the resistance to transformations that maintain spatial uniformity, leading to the development of a concept called Pairwise Transform Invariance (PTI). They introduced an approach known as PRICoLBP (Pairwise Rotation Invariant Co-Occurrence Local Binary Pattern), which integrates these novel features with rotationally invariant binary patterns to enhance robustness [10]. Local binary patterns (LBP) are recognized as potent descriptors for texture classification, but traditional LBP and its variants sometimes struggle with limited performance under restricted rotational angles. To mitigate this, Kiqiu Kwa and team developed a new local texture descriptor based on principal curvatures, called PCLBP. This descriptor combines the strengths of LBP with principal curvatures (PC) at the texture surface to improve robustness, employing a multi-resolution approach and a cross-scale encoding strategy to adjust three proportional parameters. The simplified PCLBP method is highly discriminative, invariant to changes in illumination and rotation, and offers computational simplicity [11]. Given that variations in illumination and rotation significantly affect the accuracy of texture image classification, Wei Wang and colleagues have proposed a new descriptor named Geometric Completed Local Binary Pattern (GCLBP). Drawing on the principles of continuous rotation invariance and illumination robustness from geometric curvature information, this descriptor uses principal curvatures (PC) computed for all pixels to represent the magnitude of image gradients, primarily substituting the primary gradient information in CLBP [12]. Traditional LBP descriptors, while widely used in texture analysis, are sometimes limited in capturing fully discriminative information as they rely solely on the sign bit differences within a local region. To enhance LBP's performance, Jiebin Pan and his team developed a novel texture classification descriptor called feature-based local binary pattern (FbLBP). In FbLBP, the difference vector is divided into sign and magnitude components; the sign describes the local binary pattern, while the magnitude is characterized by mean and variance features. This method is less sensitive to illumination changes and uses a local adaptive threshold to convert these features into binary codes, making it highly efficient and parameter-free for application across various databases [13]. The KNN classifier was employed for feature classification based on the distribution of extracted features. The proposed mapping methods were tested on an enhanced local binary pattern (ELBP) variant. The developed ELBP showed higher accuracy than traditional ELBP and other advanced local binary patterns. Moreover, the proposed mapping approaches improve the rotational robustness of local binary patterns, especially for larger neighborhoods. In terms of computational complexity, the new ELBP provides fewer features, significantly enhancing processing speed [14]. Rakesh Mehta et al. introduced a highly efficient and rotationally robust texture descriptor called Dominant Rotation Local Binary Pattern (DRLBP). This descriptor achieves rotation invariance by computing it based on a reference within a local region, ensuring simplicity. This reference allows quick computation of local binary patterns while maintaining comprehensive structural information. The proposed method not only preserves the complete structural information of local binary patterns but also stores additional value-based information, increasing discriminative power. Feature selection involves learning common patterns from training images and filtering out redundant, non-informative features [15]. Effective texture image identification leverages multiple visual cues from the image appearance. Local Binary Pattern (LBP) and its variants have been successful in texture description. However, due to LBP features being discrete indicators of

patterns rather than numerical values, integrating them with other distinctive features into a unified descriptor is challenging. To address the non-numerical nature of LBP patterns, Jiaopeng Hong et al. propose a numerical variant called Different Local Binary Pattern (LBPD). LBPD measures the difference of a local binary pattern from the mean structure of a specific region in the image. It is straightforward, rotationally robust, and computationally efficient. For improved performance, LBPD is combined with other distinctive cues using a covariance matrix. The proposed descriptor, Covariance-Local Binary Pattern Difference (COV-LBPD), efficiently captures the intrinsic correlations between LBPD and other features compactly. This approach aims to enhance the robustness and discriminative power of texture classification systems [16]. Jianhua Guo et al. proposed a comprehensive modeling of the Local Binary Pattern (LBP) operator and developed an enhanced framework called Completed Local Binary Pattern (CLBP) for texture classification. A local region centered on each pixel is indicated, and its Local Difference Sign Magnitude Transform (LDSMT) is demonstrated. The central pixels represent the grayscale level of the image and are transformed into a binary code, known as CLBP_C or CLBP_Center, using a global threshold. LDSMT divides local image differences into two complementary components: CLBP_Sign and CLBP_Magnitude, which are proposed for encoding. CLBP_S relates to the local binary pattern section and retains more information about the local structure compared to CLBP_M, indicating that the simple LBP operator can effectively extract texture features. By combining the features CLBP_S, CLBP_M, and CLBP_C in joint or composite distributions, significant improvements in rotationally robust texture classification can be achieved. This approach enhances the robustness of texture classification against rotation [6]. Texture image classification is crucial in computer vision research. To effectively capture texture patterns, a distinctive feature such as Local Binary Pattern (LBP) is essential. LBP is resistant to uniformity changes and grayscale variations, and its fast computation makes it popular in various texture analysis applications. However, LBP is sensitive to noise. To reduce noise effects and enhance pattern discrimination, a triple local pattern approach called Local Ternary Pattern (LTP) has been proposed. Unlike the binary encoding of LBP, LTP uses a ternary encoding scheme, making it better at tolerating noise and significantly enhancing discrimination. These advantages improve LTP's classification accuracy. This paper thoroughly examines feature extraction for robust local pattern recognition as an integer decomposition problem, formulated as a generalized version of the Bachet de Meziriac Weight Problem (BMWP). Based on this generalization, Sheng Yang et al. proposed a Local n-ary Pattern (LNP), specifically parameterized for n=2, where LBP serves as a specific case. LTP is not a specific instance of LNP. Both LBP and LTP are recognized for their success as benchmark methods for evaluating LNP performance. The proposed LNP significantly improves texture classification accuracy compared to LBP and shows considerable enhancement over LTP [17]. While LBP is sensitive to noise and LTP partially mitigates this issue, both methods perform similarly when dealing with corrupted image patterns. To address this, Jianfeng Ren et al. proposed a Noise-Resistant Local Binary Pattern (NRLBP) to preserve local structures in noisy images. Small pixels, vulnerable to noise, are first encoded as an indeterminate state and then assigned a value based on other LBP bits. Essentially, they created an error correction mechanism to recover distorted image patterns [18]. A local region in an image can be defined using its central pixel and the differences with its neighboring pixels. To effectively distinguish structures of various textures, Nishant Srivastava et al. propose a method called Noise-Invariant Structure Pattern (NISP), which uses the central pixel along with local and global information of an image. Instead of the central pixel, a computed threshold is used to add the central pixel and the mean intensity in calculating the local binary pattern code. For incorporating quantitative information, binary patterns are generated by taking thresholds related to the central pixel and local/global contrasts. Additionally, for incorporating adjacency information of a specific pixel, binary patterns are generated using global mean thresholds. The proposed method is insensitive to noise because the central pixel is not directly used as a threshold [19]. Local Binary Pattern (LBP) is considered one of the most efficient texture features with high performance. However, the traditional LBP method is highly sensitive to image noise and lacks the capability to capture information within larger structures. To address these issues, Li Liu and colleagues introduced a robust extension of LBP called Median Robust Extended Local Binary Pattern (MRELBP) for texture classification. This proposed model differs from traditional local binary patterns by utilizing regional medians instead of raw image intensities. A multi-scale local binary pattern descriptor is computed by comparing regional medians on a novel sampling pattern, effectively capturing both fine-grained and coarse-grained texture information [20]. Ticheng Song et al. propose a noise-robust descriptor for texture classification using a set of Local Contrast Patterns (LCP) through global metrics. To manage image noise, directional and non-directional difference masks are designed to compute three types of contrasts: directional, non-directional, and maximum. For pixel-level feature description, these responses are separately quantized and encoded based on various global metrics in specific patterns. The resulting patterns (LCPs) are collectively encoded to form the final representation of the proposed texture model [21]. Local Binary Pattern (LBP) is sensitive to noise and suffers from limited range detection capabilities. Despite significant advances, most types of LBP still exhibit constraints related to noise sensitivity, high dimensionality, and computational inefficiency. Addressing these issues, Jibin Pan et al. propose an adaptive local descriptor resilient to noise named Diamond Sampling Structure Based Local Adaptive Binary Pattern (DLABP). The objective is to achieve efficiency, simplicity, and speed through a structure-based sampling approach [22].

Research in texture detection often focuses on the challenging task of identifying materials under irregular conditions, a scenario rarely met by algorithms. In this work, Mircha Simpoy et al. undertake the first study to describe identifiable texture features and materials in disarray, utilizing a newly derived database from the surface tissue repository. They propose a novel texture descriptor named FV-CNN (Fisher Vector Pooling of a Convolution Neural Network), which integrates feature vectors from a convolutional neural network bank. FV-CNN is considered significantly advanced in texture detection, effortlessly

transferring across domains without the need for feature adaptation as in fully connected layers of convolutional neural networks. Moreover, FV-CNN can seamlessly combine multiscale information and describe regions of arbitrary shapes and sizes [23]. Cancer ranks among the most perilous diseases for human health. Extensive efforts have been made in radiology advancements and tools such as tumor tomography or CT (computed tomography) imaging for early cancer detection. One of the primary objectives is to distinguish malignant cancer from benign ones. In recent years, deep learning, particularly convolutional neural networks, has aided medical science in cancer identification. Deep learning algorithms invariably require large databases. However, collecting such a vast volume of images with pathological information, especially in medical imaging, particularly for cancer imaging, remains challenging. Therefore, strategies for effective learning from small databases through deep neural network models are essential. To advance this goal, Shou Zhang et al. investigate two deep neural network models with a substantial focus on expanding training samples from two proven pathological small databases for distinguishing malignant from benign cancers [24]. Designing texture features with high discriminative power and robustness under various conditions poses a significant computer vision challenge with numerous applications, including material recognition and analysis of satellite or aerial images. Historically, most texture description approaches relied on dense statistical distributions and local features. However, recent approaches for texture detection and classification in remote sensing images predominantly utilize convolutional neural networks (CNNs). The practical operation during the training of these CNN models involves using RGB channels as inputs, trained on extensive labeled datasets. In this paper, Rao Mohammad Anwar et al. present TEX-Net, a convolutional neural network model with localized binary pattern encoding. TEX-Net is trained using encoded images to map textures based on learned local binary pattern information. Additionally, they propose two deep architectures, initial and final fusion, for texture and color information integration. Their combined approach leads to improved classification of remote sensing images [25]. Reference [25-26] used signal processing techniques to improve the classification and finally, reference [27] used the CNNS for controlling applications. Recent advancements in deep learning involve analyzing CNN inference processes. [28] examined feature extraction in CNNs using principal eigenfeatures and logistic regression probes, providing insights into model interpretability. In medical imaging, [29] developed a multi-channel, multi-scale CNN for detecting cerebral microbleeds in MR images, demonstrating superior performance over conventional methods. Nonlinear feature extraction techniques have also gained attention. [30] utilized Dual-Tree Complex Wavelet Transform (DTCWT) subimages for brain MRI classification, improving disease diagnosis accuracy. Similarly, [27] proposed a hybrid Radial Basis Function (RBF) network with nonlinear ECG features to enhance sudden cardiac death prediction. The objective of this research is to implement a method based on the combination of enhanced local binary pattern and deep neural networks for classifying texture images. Despite its simplicity, local binary pattern exhibits computational complexity due to the increased local patterns, thus suggesting the need for improved local patterns that are also highly sensitive to ambiguous and noisy images. Considering that both enhanced local binary pattern and deep neural networks are essential tools for feature extraction, the aim of this research is to integrate enhanced local binary pattern with deep neural networks to enhance classification accuracy in texture classification tasks. There exists the possibility that simple networks can achieve better results through various sets of outcomes for texture classification. Instead of focusing on designing complex networks, it is felt that designing simple and efficient networks is crucial for challenges such as accuracy and speed. Therefore, exploring effective utilization of enhanced local binary pattern computations with deep learning architectures is also highly noteworthy.

2. PROBLEM STATEMENT

2.1. Introduction

In this section, we will first provide an overview of the software used to implement the necessary experiments on the proposed method. Next, we will describe the enhanced local binary pattern algorithm. Following this, a schematic of the proposed method will be presented. The aim of this section is to introduce the proposed method along with its detailed explanation.

2.2. Concept of the Proposed Method

The main idea of this model is based on the improved performance of the enhanced local binary pattern (LBP) algorithm and deep neural networks in feature extraction from texture images. Each of these methods extracts the desired features from texture images and connects each other. Unlike other images, texture images often cannot be processed as grayscale levels due to their complexity and significant brightness variations. Moreover, most preprocessing methods are not applicable to textures and may result in the loss of the original texture data. The texture of any object is a collection of image points that form a pattern with either repetitive or non-repetitive structures. The two main issues related to texture images are texture classification and segmentation. Texture classification plays a crucial role in several fields. The most important part of texture processing is feature extraction, for which various methods exist. The local binary pattern (LBP) and its enhanced form are used in both texture detection and classification. In LBP, a non-parametric method, the number of neighboring points (P) and the neighborhood radius R must be specified. The number of extracted features in this method is 2^P. One problem with LBP methods is their sensitivity to image scaling; methods have been developed to address this, making them insensitive to the rotation and scaling of texture images. Additionally, convolutional neural networks (CNNs) are among the leaders in image processing. In the next section, it will be demonstrated that the combination of the enhanced local binary pattern and convolutional neural networks has been effectively implemented.

2.3. Selection of Programming Language for Model Implementation

After extensive studies on the methods described in the previous sections, it is necessary to implement each method using a programming language and then test it with

appropriate data. The proposed method has been implemented using the Python programming language within the Jupyter Notebook environment. Python (Python - Machine Learning Developer Completed Local Binary Pattern) is a simple and efficient programming language that offers numerous frameworks for machine learning. It is a high-level language that, despite its simplicity, provides a wide range of capabilities to machine learning specialists, enabling them to easily implement their objectives. The computer system used for the implementation of the proposed model is detailed below in Table 1.

2.4. Introduction to the Completed Local Binary Pattern

In this code, we use the *CLBP* (Completed Local Binary Pattern) method. Unlike other methods that only use the sign of the difference in the binary pattern, *CLBP* utilizes both the sign (*CLBP_S*) and the magnitude of this difference (*CLBP_M*). Additionally, it incorporates the information from the central pixel (*CLBP_C).* By combining these three types of information, this method achieves a high classification accuracy. As mentioned, CLBP extracts three types of LBP: *CLBP_S* is the same as $LBP_{P.R}^{riu2}$, which is generated from the sign of the comparison between the central point and its neighbors. *CLBP_M* represents the magnitude of the difference between the center and its neighbors. If this magnitude is greater than or equal to a certain threshold—the mean of neighborhood—it is coded as 1; otherwise, it is coded as 0 for *CLBP_M*. *CLBP_C* is derived from the central points; if this point is greater than or equal to the overall image mean, it is coded as 1; otherwise, it is coded as 0. Numerous combinations of these three histograms are produced, the most well-known being *CLBP_S/M* and *CLBP_S/M/C*. In this code, we have considered all combinations. The overall implementation of CLBP is based on Fig. 1. Previous sections have provided explanations regarding the operation of Fig. 1.

3. Proposed Method

This model is divided into two parts. In the first part, the image is input into the convolutional network. The convolutional layer is applied to create a feature map. A max pooling layer is then applied to the generated feature maps, and this process is repeated two more times to ensure the network is well-trained and produces diverse feature maps. In the second part, the image is input into the Completed Local Binary Pattern (CLBP) algorithm, and the output is fed into a convolutional neural network with lesser depth to effectively extract the desired features. The features from the aforementioned two parallel parts are then separately flattened using a Flatten function, allowing them to be combined. This property of deep neural networks and CLBP enables the integration of these two tools by flattening their generated feature maps. The combined vector is then fed into a fully connected artificial neural network.

The features are processed through the network, and the final fully connected layer begins to prioritize and vote on the classes we are targeting. Training is conducted through backpropagation over multiple epochs until a well-defined neural network with trained weights and desired features is obtained. This process continues until the best accuracy is achieved, as predetermined by the epochs set for the model. The classification accuracy is then displayed using the test data. The proposed model is a unique approach that effectively combines the Completed Local Binary Pattern (CLBP) and deep neural networks, yielding acceptable results. The schematic of the proposed model is presented in Fig. 2. In this model, the features extracted by the Concatenate Local Binary Pattern (LBP) and convolutional neural networks are used for texture image classification. The features of the proposed method in this paper include:

1. High accuracy
2. Image brightness sensitivity
3. Insensitivity to brightness variations
4. Image noise sensitivity
5. Relatively good speed

3.1. Calculation of Accuracy of Classification

To classify images, half of them are designated for training purposes, while the other half constitutes the testing dataset. The criterion for comparing each method against another is the accuracy of their classification. Even though more test images are correctly classified, the accuracy and performance of the evaluated method are further investigated. To assess the accuracy of method performances in tissue classification, the ratio of correctly classified images to the total number of test images, either or the test data, is utilized. This ratio percentage indicates the classification accuracy of the method employed. This value is employed in experiments to compare each method with others. Eq. (4-1) represents the method for calculating the classification accuracy of tissues in each method [14].

$$Accuracy = S/t * 100 \quad (1)$$

In this formula, S represents the number of images correctly classified, and T represents the total number of test images or the number of test data.

Table 1: Specifications of the System used.

CPU	Intel Core i5 7th Gen
hard disk	500 GB
Memory	4 GB
operation system	Windows
The used software	Jupyter notebook-python

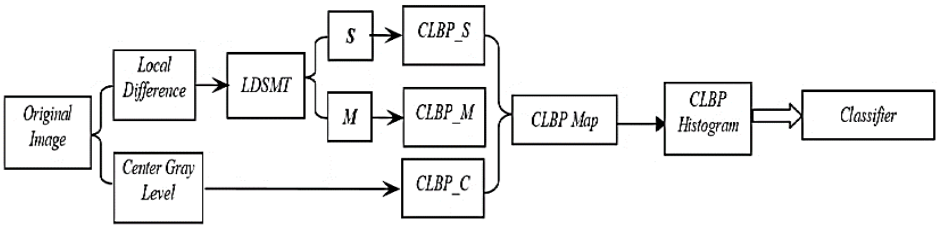


Fig. 1: Operation of CLBP [14].

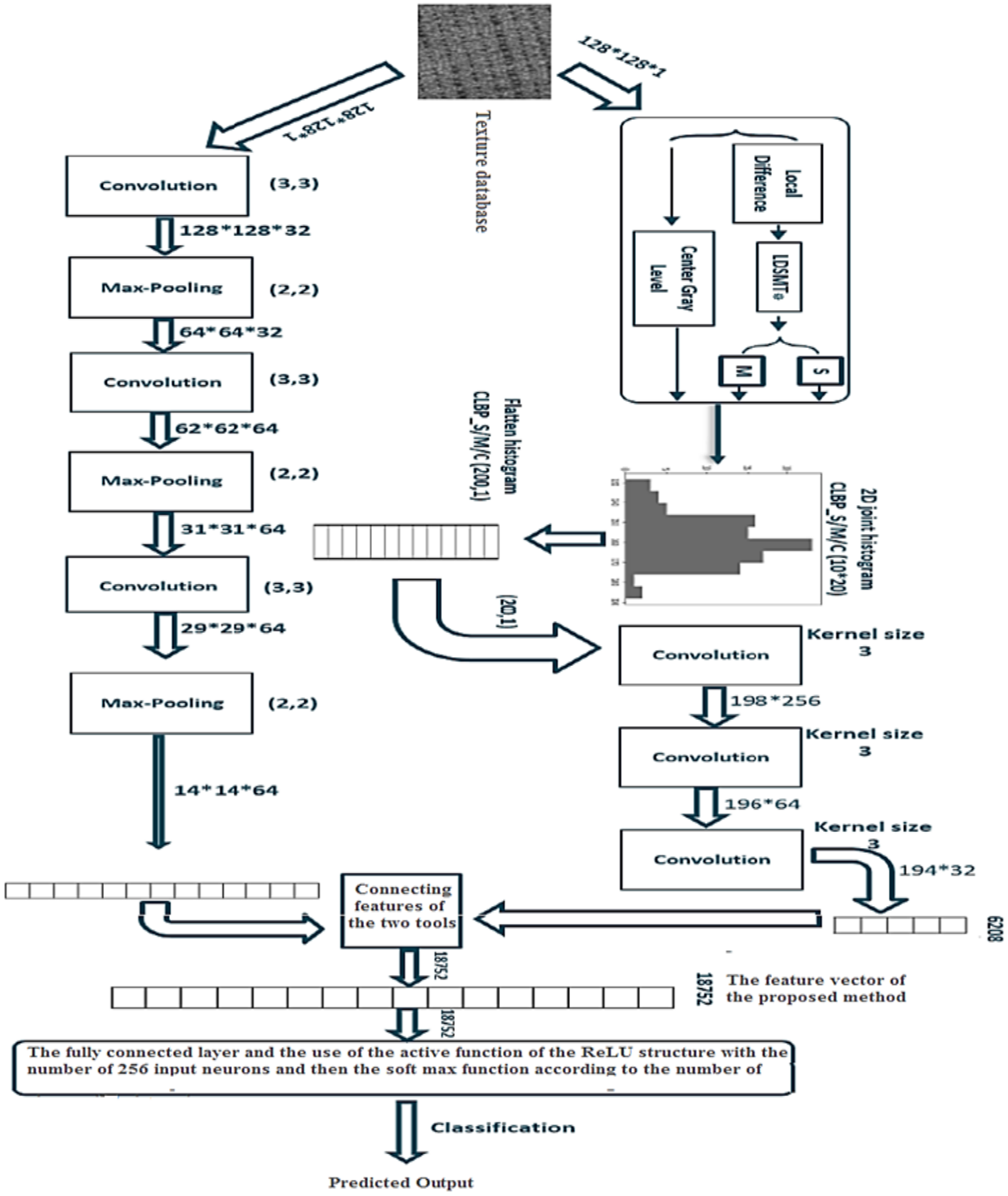


Fig. 2: Schematic of the proposed model.

4. RESULTS AND ANALYSIS

4.1. Introduction

In this section, we first examine the specifications of the databases used for conducting necessary experiments on the proposed methods. Subsequently, the outputs obtained from these experiments are presented in the form of tables. Finally, we will discuss each of the tables and the obtained results.

4.2. Introduction of the Database Used

After selecting the simulator and presenting the proposed method, each method is tested with appropriate data. In this paper, images from the *Outex* and *CUReT* databases are used for experimentation. The features of these databases will be discussed further. It is worth noting that in most of the reviewed literature on the subject under study, these databases have been used for testing and evaluating proposed

methods. Therefore, it can be concluded that the outputs obtained from the analyzed data can be considered reliable.

4.2.1. *Outex database*

It provides a framework for empirical evaluation of texture classification algorithms. This image database includes a large collection of textures, both surface textures and natural scenes. The surface textures exhibit specific variations in terms of lighting, rotation, and spatial resolution for a given reference. Reliable manual classification of natural scenes is incorporated into the ground truth data. Each database selects 24 different classes of homogeneous textures, each with a size of 128 × 128 pixels. Due to its extensive variety of textures, this database poses significant challenges. The *Outex* images were initially analyzed by Ojala et al. (2002) using a subset of texture features. The experiments in this section were conducted on the TC10 and TC12 databases from the *Outex* database bank. These two groups include 24 classes of different textures under three different lighting conditions: horizontal, tl84, and *inca*, and at 9 orientations (0, 5, 10, 15, 30, 45, 60, 75, and 90 degrees). For each class under each condition, there are 20 samples of 128x128 pixels. The detailed descriptions of these two databases are as follows.

- *TC10 database*

The *TC10* database utilizes *inca* lighting conditions. Images at zero degrees from each class are used for training in the classification task. Images at eight other angles are employed as test data. This database contains a total of 480 models (20*8*24) for training and 3840 valid samples (20*8*24), summing up to 4320 images.

- *TC12 database*

In this type of database, classification is trained with similar data as *TC10*, and it is tested with samples under *tl84* or *horizon* lighting conditions.

A selection of images from the *Outex* database is presented in Fig. 3 as sample images of the *Outex* database.

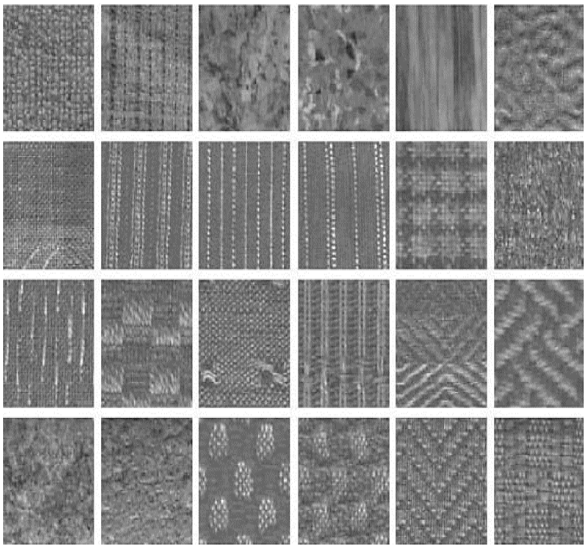


Fig. 3: Sample images of the *Outex* database.

4.2.2. *The CUReT database*

This database was created by researchers from Columbia University and Utrecht University, comprising 61 texture samples from various materials, each containing 92 images. Each image measures 200 × 200 pixels and was captured under controlled laboratory conditions at Columbia University. Unlike the *Outex* database, the images in *CUReT* are unlabeled. In the proposed method, half of the 5612 images available in this database are used for training, and the other half for testing. Similarly, for ease of work in the *Outex* database, half of the data is allocated to training and the other half to testing.

From the images of the *CUReT* database, a selection has been made, as depicted in Fig. 4: Sample Images of the *CUReT* Database. The specifications of the desired databases are summarized briefly in Table 2.

The aim of the proposed method is to enhance the classification robustness against rotations, lighting variations, and scale changes. Therefore, the proposed method needs to be tested on images with different rotations, scales, and lighting conditions. These two well-known databases serve as suitable benchmarks to evaluate the proposed method.

4.3. Training Specifications

In this section, the parameter specifications during training will be presented. The number of epochs for running the proposed model is set to 25, which seems appropriate for training the model effectively. The batch size, which corresponds to the number of images sent for training, is set to 12, meaning each training batch contains 12 images. The L2 regularization method is used ideally to adjust the weights. *EarlyStopping* technique is employed to prevent overfitting during the model execution. The *Adam* optimization method is utilized throughout the training process. The primary metric for evaluation, indicating correctness or incorrectness, is the accuracy. Additionally, the *shuffle* parameter during training is set to *true*, ensuring that sufficient information about the training progress is provided to the network architecture.

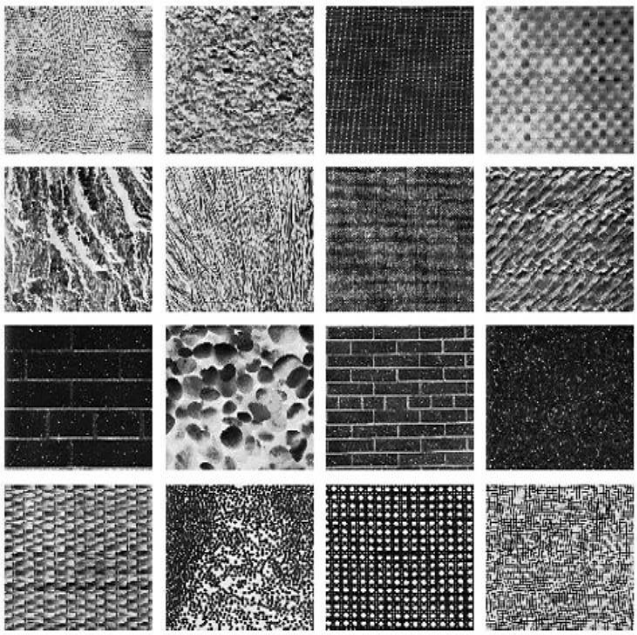


Fig. 4: Sample images of the CUReT database.

Table 2: Specifications of the *Outex* and *CUReT* databases.

Database Name	Dimensions of Image	Number of Classes	Number of Samples per Class	Including Training/Test segmentation	Number of Training Samples per Class	Number of Test Samples per Class	Characteristics
Outex-TC10	128x128	24	20	Yes	20	20	Images with inca lighting and 0-degree angle for training
Outex-TC12	128x128	24	20	Yes	20	20	Images with inca lighting and 0-degree angle for training. With two conditions tl84 and horizon
CUReT	200x200	61	92	No	46	46	Varied lighting conditions, small rotations, shadows, and angle changes in image acquisition

4.4. Experimental Results

In this section, the proposed method is experimented with the specified databases described earlier. The outputs of these experiments are numerical values representing the classification accuracy of each method under different conditions, expressed as percentages. Essentially, this value indicates the ratio of correctly classified images to the total number of images tested or the testing data.

4.5. Drawing Conclusions from Experimental Results

The results are presented in the form of tables. Each table column is divided into three sections: classification, radius, and different numbers of neighboring pixels are considered in each section. Table 3, which corresponds to the *Outex* database, considers a radius of one and eight neighboring pixels in the first section, a radius of two and sixteen neighboring pixels in the second section, and a radius of three and twenty-four neighboring pixels in the third section. Experiments in each section were conducted with different radius and neighboring pixel configurations for each database. As described in the *TC12* database section, this database contains images under two illuminations: *tl84* and *horizon*. Experiments were conducted separately on each of these illuminations, and the results are listed in two columns labeled *t* (*tl84*) and *h* (*horizon*). Therefore, in each section, the first column displays the results of experiments on the *TC10* database, and the second and third columns show the results of experiments on the *TC12* database under tl84 and horizon illuminations. Subsequently, the average of these three columns is provided in the fourth column of each section.

In Table 4, which pertains to the *CUReT* database, similar to the *Outex* database table, a radius of one and eight neighboring pixels is considered in the first section, a radius of two and sixteen neighboring pixels in the second section, and a radius of three and twenty-four neighboring pixels in the third section. Experiments in each section were conducted with different radius and neighboring pixel configurations on the database. The average of the three columns is shown in the fourth column. The proposed model combining *CLBP_S/M/C+CNN*, as well as combinations *CLBP_S/M+CNN* and *CLBP_S_M/C+CNN*, achieved good classification accuracy and performed well under various conditions. Next, we compare the proposed method with previous methods. In all previous methods, the highest accuracy values were obtained using these operators, namely *CLBP_S/M/C*, *CLBP_S/M*, and *CLBP_S_M/C*, and the results obtained were not unexpected. Combining these operators with deep neural networks yielded the best performance.

4.6. Results of Comparing the Proposed Method with Previous Methods

The proposed model has significantly improved classification accuracy compared to all previous methods. The enhanced separability power is attributed to the utilization of combined features of local binary pattern (LBP) patterns and the desired neural network. The classification accuracy of the proposed model has notably increased compared to all past methods, which mainly rely on single-feature extraction methods. One distinctive aspect of this model is its utilization of a deep neural network, distinguishing it from previous models. While convolutional neural networks (CNNs) have also been employed for texture classification, the dataset used differs from those in this study, resulting in relatively lower accuracies. To ensure fairness, Table 5 was used for an impartial comparison.

Fig. 5 displays a chart created from Tables 4 to 5. The y-axis of the chart represents previous methods and the proposed model, while the *x*-axis depicts classification accuracy. Different colors are used to represent the utilized datasets. Clearly, it can be observed that the first category, indicating the proposed method, has achieved higher performance and accuracy in classification under various conditions.

4.7. Results of Experiments on Other Metrics

In Fig. 6, one of the experiment results is graphically presented using the *Matplotlib* library, illustrating the accuracy and loss of training and test data. The x-axis in each of the four images represents the epoch parameter, consistently set to 25, as observed in the figure. The y-axis displays the accuracy and loss rates. From Fig. 6, it can be concluded that the model has significantly converged, demonstrating notable accuracy and loss rates.

Table 3: Classification rates (%) in the *Outex* dataset.

	(P.R)=(8,1)				(P.R)=(16,2)				(P.R)=(24,3)			
	TC10	TC12		AVG	TC10	TC12		AVG	TC10	TC12		AVG
		t	h			t	h			t	h	
CLBP_S+CNN	87.93	79.08	81.35	82.78	88.10	81.41	83.71	84.40	90.54	80.24	81.42	84.06
CLBP_M+CNN	83.64	64.48	68.12	72.08	89.41	86.73	85.91	87.35	91.22	81.02	80.71	84.31
CLBP_M/C+CNN	93.04	85.77	89.92	89.57	97.22	97.22	91.46	94.19	97.84	92.05	94.95	94.94
CLBP_S_M/C+CNN	99.25	93.68	94.21	95.71	99.25	94.27	96.61	96.71	99.71	97.20	96.82	97.91
CLBP_S/M+CNN	99.67	98.20	97.77	98.54	99.75	91.30	93.47	94.84	98.77	97.48	97.09	97.78
CLBP_S/M/C+CNN	99.86	98.61	98.24	98.90	99.80	98.66	98.97	99.14	98.75	98.78	98.03	98.52

Table 4: Classification rates (%) of the model on the CUReT dataset.

	(P.R)= (8,1)	(P.R)= (16,2)	(P.R)= (24,3)	
	CUReT	CUReT	CUReT	AVG
CLBP_S+CNN	87.32	94.01	95.20	92.17
CLBP_M+CNN	82.63	91.37	93.81	89.27
CLBP_M/C+CNN	95.71	96.84	97.12	96.55
CLBP_S_M/C+CNN	96.57	97.06	97.40	96.55
CLBP_S/M+CNN	97.84	98.76	98.81	98.47
CLBP_S/M/C+CNN	99.07	98.93	99.11	99.03

Table 5: Comparison of similar methods with the proposed method.

	Method Name	Database				Mean of Accuracy
		TC10	TC12"t"	TC12"h"	CUReT	
1	CLBP [6]	99.14	95.18	95.55	97.39	96.81
2	Yang [8]	-	97.08	95.99	-	96.53
3	SLGP [9]	97.79	84.17	83.82	94.83	90.15
4	PRICoLBP [10]	94.48	92.75	92.50	-	93.24
5	PCLBP [11]	99.61	97.52	96.16	95.34	97.15
6	NRLBP [18]	93.44	86.13	87.38	83.08	87.50
7	NISP [19]	99.19	96.97	96.93	95.81	97.22
8	LNP [15]	94.97	80.93	83.77	91.25	87.73
9	LCP [21]	98.65	96.18	97.34	95.49	96.91
10	GCLBP [17]	99.48	98.26	98.87	97.56	98.54
11	FbLBP [13]	99.87	97.38	96.60	97.86	97.92
12	EMCLBP [14]	99.61	96.37	95.32	95.17	96.61
13	DRLB P [20]	99.19	97.15	95.37	90.77	95.62
14	COV-LBPD [16]	98.78	95.72	97.62	-	97.37
15	Proposed Method	99.86	98.78	98.91	99.11	99.16

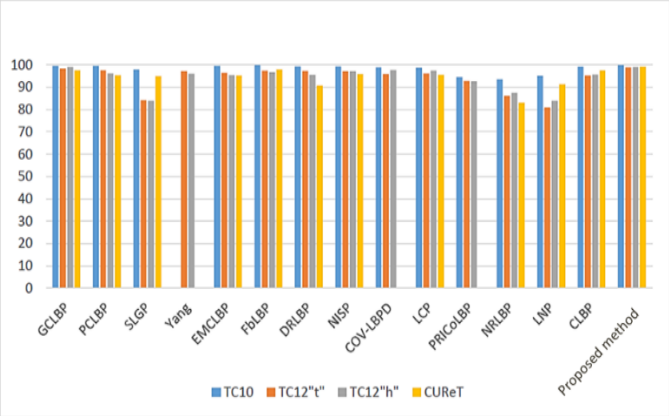


Fig. 5: Comparison chart of accuracy between the proposed model and previous models.

In all articles, other metrics are examined for evaluating the model, with the most important ones being *precision*, *recall*, and *f1-score*. The maximum value for these metrics is 1, and the minimum value is 0. This paper also utilizes these metrics to evaluate the proposed model. Table 6 illustrates that the model was able to classify 24 classes with acceptable accuracy. The fourth column labeled "*support*" indicates the number of images sent for each class in the experiment, which follows a numerical algorithm but does not significantly differ among the classes.

5. CONCLUSION

The local binary pattern (LBP) model is a straightforward approach. This method generates local binary codes from image textures and utilizes their histograms for texture classification. While simple, this approach exhibits limited robustness against noise and imposes a high implementation complexity due to the large number of possible states it produces. Therefore, an improved local binary pattern (LBP) model has been proposed in this study, which uses a uniformity measure to significantly reduce the complexity of the original LBP pattern. Additionally, it appears that combining the improved LBP pattern with deep neural networks enhances classification accuracy according to the proposed model, making the process simpler. This research introduces a novel architecture for texture image

Table 6: Accuracy in metrics of precision, recall, and f1-score.

	Precision	Recall	F1-Score	Support
0	1.00	1.00	1.00	80
1	1.00	1.00	1.00	80
2	1.00	1.00	1.00	89
3	0.99	1.00	0.99	94
4	1.00	1.00	1.00	82
5	1.00	1.00	1.00	98
6	1.00	1.00	1.00	90
7	1.00	1.00	1.00	85
8	1.00	1.00	1.00	83
9	1.00	1.00	1.00	98
10	1.00	1.00	1.00	95
11	1.00	1.00	1.00	78
12	1.00	1.00	1.00	81
13	1.00	1.00	1.00	91
14	1.00	0.99	0.99	84
15	1.00	1.00	1.00	84
16	1.00	1.00	1.00	86
17	1.00	1.00	1.00	89
18	1.00	1.00	1.00	84
19	0.98	1.00	0.99	97
20	1.00	1.00	1.00	83
21	1.00	1.00	1.00	84
22	1.00	1.00	1.00	79
23	1.00	0.97	0.99	79
Accuracy			1.00	2073
Macro Avg.	1.00	1.00	1.00	2073
Weighted Avg.	1.00	1.00	1.00	2073

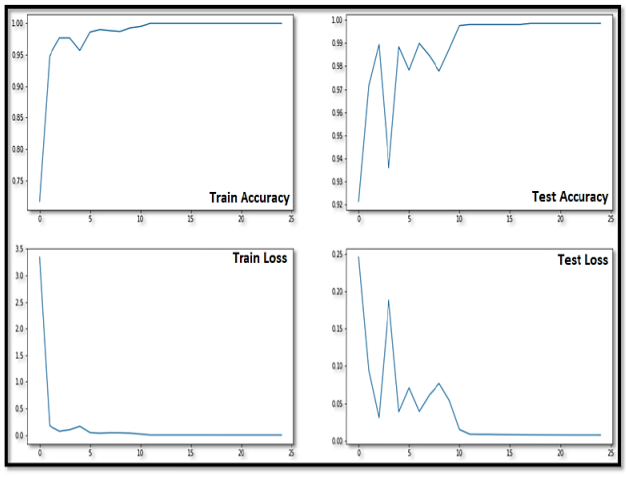


Fig. 6: Graphical representation of accuracy and loss of training and test data.

classification using the enhanced local binary pattern (LBP) model and deep neural networks. The proposed model was evaluated on the *Outex* and *CUReT* databases using various improved local binary pattern (LBP) methods, and its best results were reported and compared with previous approaches. The proposed model demonstrates a superiority of 1% to 10% in classification accuracy compared to previous models. Considering the types of databases used for implementing this model, it can be concluded that the introduced model may yield similar results on other texture image databases. Moreover, the deep neural network utilized for this task was unique in its own right and differed from other well-known networks. In this model, both the deep neural network and the enhanced local binary pattern (LBP) method focused on feature extraction, and the extracted features were subsequently connected.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Behzad Abbasi: Conceptualization, Roles/Writing - original draft, Writing - review & editing. **Majid Ghandchi**: Project administration, Supervision, Validation, Writing - review & editing. **Sirous Tannaz**: Supervision, Validation. **Javad Ostadieh:** Resources, Writing - review & editing. **Saeed Barghandan:** Methodology, Project administration, Supervision, Validation.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues; including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy has been completely observed by the authors.

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