© MAR 2026 | IRE Journals | Volume 9 Issue 9 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I9-1715162

Machine Learning–Based Texture Classification Using Sorted Consecutive Local Binary Pattern Features

DR. A. SRIKRISHNA[1], S. DIVIJA LAKSHMI[2], M. CHETANYA LAHARI[3], S K. SAMEER[4], T. PRASANNA LAKSHMI[5]

[1]*Professor, Department of IT, R.V.R & J.C.C.E Guntur, India*

[2,3,4,5]*Final Year Students, Department of IT, R.V.R & J.C.C.E Guntur, India*

Abstract– Texture classification is a fundamental task in computer vision and image analysis, widely used in applications such as medical imaging, material inspection, remote sensing, and object recognition. Among various texture descriptors, Local Binary Pattern (LBP) has gained significant attention due to its simplicity and computational efficiency. However, conventional LBP methods often ignore certain binary patterns with multiple transitions, which may lead to loss of important texture information. To overcome this limitation, this paper presents a machine learning based texture classification approach based on Sorted Consecutive Local Binary Pattern (scLBP). The proposed method extracts local texture features by analyzing binary relationships between neighboring pixels and sorting consecutive patterns to preserve detailed structural information. The extracted scLBP feature vectors are then used as input to a machine learning classifier for texture recognition. Experimental analysis shows that the proposed approach provides improved feature representation and achieves better classification performance compared with traditional LBP-based techniques. The results demonstrate that the scLBP-based framework can effectively enhance texture classification accuracy and robustness.

Index Terms -- Texture Classification, Local Binary Pattern (LBP), Sorted Consecutive Local Binary Pattern (scLBP), Machine Learning, Image Processing.

I. INTRODUCTION

Texture analysis plays an important role in many computer vision and image processing applications. It helps in identifying and categorizing surfaces based on their visual patterns and structural properties. Texture classification is widely used in areas such as medical image analysis, industrial inspection, remote sensing, material recognition, and object detection. The ability to accurately analyze texture information can significantly improve the performance of automated image understanding systems.

Among the various techniques proposed for texture analysis, the Local Binary Pattern (LBP) operator has become one of the most popular methods. LBP is widely adopted because of its simplicity, computational efficiency, and ability to effectively describe local texture structures. The method works by comparing a center pixel with its neighboring pixels and generating a binary pattern that represents the local intensity relationship. These binary patterns are then used to construct histograms that serve as texture descriptors.

Although LBP has been successfully applied in many applications, it also has certain limitations. Traditional rotation-invariant LBP methods often consider only a subset of possible patterns, particularly those with limited transitions between binary values. Patterns containing more complex transitions are usually grouped together or ignored, which may lead to loss of valuable texture information. As a result, the discriminative ability of the descriptor may decrease when dealing with complex or highly varied textures.

To address this limitation, the Sorted Consecutive Local Binary Pattern (scLBP) descriptor has been introduced as an improved approach for texture representation. Unlike conventional LBP-based methods, scLBP preserves all possible binary patterns and analyzes them based on their consecutive relationships. By sorting consecutive patterns, scLBP is able to capture more detailed structural information from texture images. This allows a richer representation of local image features and improves the effectiveness of texture classification.

In this work, a machine learning–based texture classification framework using scLBP features is presented. The proposed system extracts texture descriptors using the scLBP method and then applies machine learning algorithms to classify the texture images. The use of machine learning techniques helps in learning complex decision boundaries and improves classification accuracy.

The main objective of this study is to investigate the effectiveness of scLBP features for texture classification and to evaluate their performance using machine learning classifiers. Experimental analysis demonstrates that the proposed approach provides improved texture representation and achieves better classification performance compared with traditional LBP-based techniques.

II. RELATED WORK

Texture classification is an important research area in computer vision and image processing. Various feature extraction techniques have been developed to represent texture patterns effectively by analyzing the spatial relationships between pixels in an image [5], [10].

One of the most widely used methods for texture analysis is the Local Binary Pattern (LBP). The LBP operator describes local texture structures by comparing the intensity of a center pixel with its neighboring pixels and generating a binary pattern. Due to its simplicity and computational efficiency, LBP has been widely applied in applications such as face recognition, medical image analysis, and surface inspection[1],[11].

To improve the descriptive capability of LBP, several extensions have been proposed. One of the important extensions is the Complete Local Binary Pattern (CLBP). The CLBP method enhances the traditional LBP by incorporating additional information such as the magnitude of local differences and the center pixel intensity. In CLBP, the local texture representation is divided into three components: the sign component, the magnitude component, and the center pixel component. These components capture more detailed information about local image structures and improve the discriminative power of the texture descriptor. By combining these components, CLBP provides a more comprehensive representation of texture patterns and improves classification performance compared to the traditional LBP method[2].

Local Ternary Pattern (LTP) is an extension of the traditional Local Binary Pattern designed to improve robustness against noise and illumination variations. Unlike LBP, which generates binary patterns by comparing the center pixel with its neighbors, LTP introduces a threshold value to produce ternary patterns. The neighboring pixel values are compared with the center pixel using this threshold, resulting in three possible values: −1, 0, and 1. This approach helps reduce the effect of small intensity fluctuations and makes the descriptor more stable in noisy conditions. As a result, LTP provides improved performance for texture analysis in images affected by illumination changes or noise[3].

Despite these improvements, many LBP-based descriptors still ignore certain complex binary patterns containing multiple transitions. To address this limitation, the Sorted Consecutive Local Binary Pattern (scLBP) method was introduced. The scLBP descriptor considers all possible binary patterns and organizes them based on consecutive relationships, allowing it to capture more detailed structural information and improve texture classification performance [4].

Table I. Comparison of LBP-Based Texture Descriptors

Property	LBP	CLBP	scLBP
Captures Local Texture	Yes	Yes	Yes
Rotation Handling	No	Partial	Improved
Feature Complexity	Low	Medium	Medium
Discriminative Power	Low	Medium	High
Classification Performance	Moderate	Good	High

Table I compares different LBP-based texture descriptors and shows that the scLBP method provides improved discriminative capability and better classification performance.

III. PROPOSED METHODOLOGY

This section explains the overall framework used for texture classification using Sorted Consecutive Local Binary Pattern (scLBP) features. The proposed system focuses on extracting discriminative texture features from images and using machine learning techniques to classify different texture categories. The complete workflow consists of several stages including image acquisition, preprocessing, feature extraction using scLBP, feature vector generation, and classification.

A. Overall Framework of the Proposed Method

The proposed texture classification system follows a structured pipeline to analyze and classify texture images. Initially, texture images are collected from a dataset and prepared for processing. After preprocessing, the scLBP method is applied to extract local texture patterns from the image. These patterns are converted into feature vectors that represent the texture characteristics. Finally, machine learning classifiers such as Support Vector Machine (SVM) or K-Nearest Neighbour (KNN) are used to classify textures into their respective categories. The overall processing pipeline of the proposed scLBP-based texture classification system can be represented as follows:

Texture Dataset → Preprocessing → scLBP Feature Extraction → Feature Vector Generation →

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DOI: https://doi.org/10.64388/IREV9I9-1715162

SVM/KNN Classification → Final Texture Category

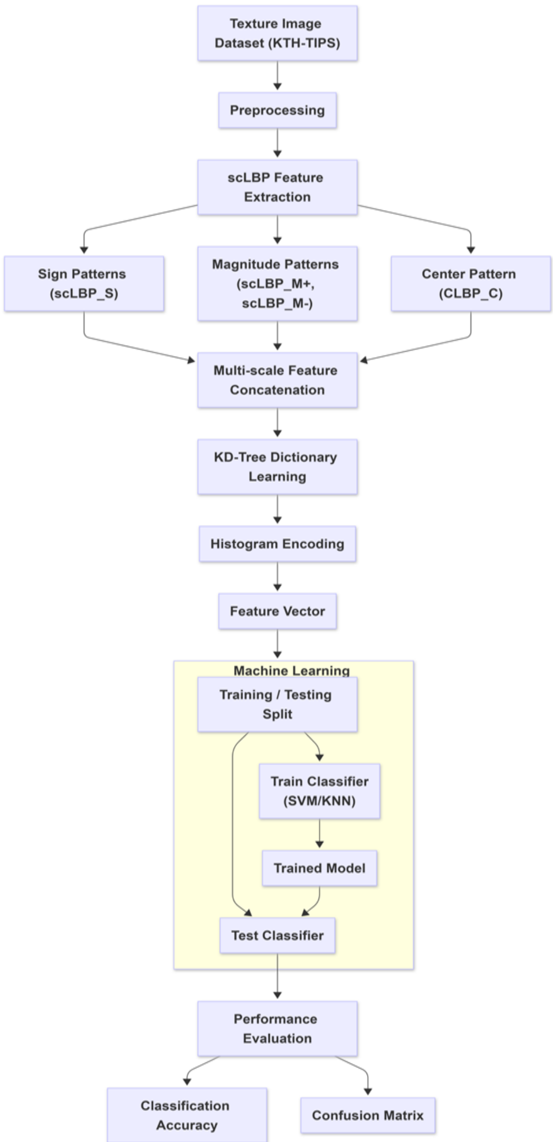

Fig 1: Overall Flowchart of the Proposed scLBP-based texture classification system.

B. Image Acquisition and Preprocessing

The first step of the system involves collecting texture images from standard texture datasets. These images represent different surface patterns such as fabric, wood, stone, and other materials.

Before feature extraction, the images are preprocessed to ensure consistent input quality. Preprocessing generally includes converting the images into grayscale format and applying basic noise reduction techniques if necessary. Converting images to grayscale simplifies the analysis process by focusing on intensity variations rather than color information.

Normalization may also be applied to maintain uniform image intensity values across the dataset.

C. Local Binary Pattern (LBP)

Local Binary Pattern is a widely used texture descriptor that captures local structural information from images. The LBP operator works by comparing the intensity value of a central pixel with its surrounding neighboring pixels.

For each neighboring pixel, a binary value is assigned based on the comparison:

- If the neighboring pixel intensity is greater than or equal to the center pixel, the value is assigned as 1.
- Otherwise, the value is assigned as 0.

These binary values form a binary pattern around the central pixel. The binary pattern is then converted into a decimal number that represents a local texture feature. By repeating this process for every pixel in the image, a distribution of LBP patterns can be obtained.

$$\text{LBP}(x_c, y_c) = \sum_{p=0}^{P-1} s(g_p - g_c) * 2^p$$

where:

- g_c = intensity of center pixel
- g_p = intensity of neighbouring pixel
- P = number of neighbors
- $s(x)$ = threshold function

Threshold function:

$$s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases}$$

Although LBP is simple and effective, it may discard important information by grouping complex patterns together.

D. Sorted Consecutive Local Binary Pattern (scLBP)

Sorted Consecutive Local Binary Pattern is an improved version of the traditional LBP method. The main idea behind scLBP is to preserve all binary patterns and organize them based on consecutive relationships rather than ignoring complex transitions.

In the scLBP approach, the binary patterns obtained from the LBP operator are analyzed to identify consecutive sequences of binary values. These sequences are then sorted to create a stable representation of texture patterns.

The process of scLBP begins by computing the LBP code for each pixel in the image. The generated binary patterns are then examined to identify consecutive runs of 0s and 1s. These patterns are sorted based on their consecutive relationships to form a structured representation. Finally, histogram features are generated from the sorted patterns and used as feature vectors for texture classification.

The scLBP descriptor typically consists of multiple components that capture different aspects of texture information:

- scLBP_S – Sign component representing the basic binary pattern.
- scLBP_M+ – Positive magnitude component.
- scLBP_M− – Negative magnitude component.
- CLBP_C – Center pixel intensity component.

By combining these components, scLBP provides a more detailed and robust representation of local texture structures.

E. Feature Vector Generation

After extracting scLBP patterns from the image, a histogram-based representation is constructed. The histogram counts the occurrence frequency of each pattern within the image.

This histogram forms a feature vector that represents the texture characteristics of the image. The feature vector captures important statistical information about the texture patterns and serves as the input for the classification stage.

$$H(i) = \sum_{x=1}^{N} \sum_{y=1}^{M} I(LBP(x,y) = i)$$

where:

- $H(i)$ = histogram value
- I = indicator function
- N x M = image size

F. Texture Classification Using Machine Learning

Once the feature vectors are generated, machine learning classifiers are used to categorize the texture images. Machine learning algorithms are capable of learning complex relationships between features and class labels.

In this work, classifiers such as Support Vector Machine (SVM) and KD-Tree based methods can be used for classification. The classifier is trained using labeled texture images so that it can learn the distinguishing features of different texture categories.

During the testing phase, the trained model predicts the class label of new images based on their extracted feature vectors.

The combination of scLBP feature extraction and machine learning classification provides an effective framework for accurate texture recognition.

F. Algorithm: scLBP-Based Texture Classification Using SVM and KNN

Input: Texture image dataset D and a test image
Output: Predicted texture class

Steps:

1. Acquire texture images from the dataset.
2. Convert each input image into grayscale format.
3. Apply preprocessing techniques such as normalization or noise reduction if required.
4. For each pixel in the image:
   a) Compare the intensity of the center pixel g_c with neighboring pixels g_p.
   b) Assign binary values using the threshold function.
5. Generate the Local Binary Pattern (LBP) code for each pixel.
6. Apply Sorted Consecutive Local Binary Pattern (scLBP) to organize the binary patterns and capture consecutive transitions.
7. Construct a histogram of the scLBP patterns to form the feature vector.
8. Divide the dataset into a training set and testing set.
9. Train the Support Vector Machine (SVM) classifier using the extracted feature vectors.
10. Train the K-Nearest Neighbor (KNN) classifier using the same feature vectors.
11. Use the trained models to classify the test images.
12. Compare the classification performance of SVM and KNN using accuracy.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

This section presents the experimental evaluation of the proposed texture classification method based on Sorted Consecutive Local Binary Pattern (scLBP). The goal of the experiment is to analyze the effectiveness of the proposed feature extraction technique and evaluate its performance in classifying different texture categories.

A. Dataset Description

The experiments were conducted using the KTH-TIPS texture dataset, which is widely used for evaluating texture classification algorithms. The dataset contains images of different material surfaces captured under varying scales, illumination conditions, and viewpoints. These variations make the dataset suitable for testing the robustness of texture descriptors.

In this work, the images are first converted to grayscale and then processed using the proposed scLBP feature extraction method. The dataset is divided into training and testing sets to evaluate the classification performance.

The dataset is divided into two parts:

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DOI: https://doi.org/10.64388/IREV9I9-1715162

- Training dataset, used for training the machine learning classifier.
- Testing dataset, used for evaluating the classification performance.

All images are converted into grayscale format before applying the feature extraction process.

Table II. KTH-TIPS Dataset Description

Parameter	Description
Dataset Name	KTH-TIPS Texture Dataset
Number of Classes	10
Image Format	PNG
Variations	Scale, Illumination, and Viewpoint
Feature Extraction Method	Sorted Consecutive Local Binary Pattern (scLBP)
Classification Methods	SVM, KNN
Dataset Split	Training Set and Testing Set
Texture Categories	Cracker, Cotton, Linen, wood, wool, lettuce_leaf, cork, corduroy, aluminium_foil, brown_bread, white_bread

Table II shows the basic characteristics of the KTH-TIPS dataset used for evaluating the proposed scLBP-based texture classification method.

B. Feature Extraction and Classification

The proposed system extracts texture features using the Sorted Consecutive Local Binary Pattern (scLBP) method. The scLBP operator analyzes the relationship between neighboring pixels and generates binary patterns that describe the local texture structure.

After extracting the scLBP features, histogram-based feature vectors are generated for each image. These feature vectors represent the statistical distribution of texture patterns within the image.

The generated feature vectors are then used as input to machine learning classifiers such as Support Vector Machine (SVM) and K–Nearest Neighbour (KNN). The classifier is trained using labeled samples from the training dataset and later used to classify unknown texture images.

C. Performance Evaluation Metrics

The performance of the proposed texture classification system is evaluated using classification accuracy. Accuracy measures the percentage of correctly classified images among the total number of test images.

The classification accuracy is calculated using the following formula:

$$\text{Accuracy} = (\text{Number of Correctly Classified Images} / \text{Total Number of Test Images}) \times 100$$

Higher accuracy indicates better performance of the texture classification method.

D. Comparison with Existing Methods

To analyze the effectiveness of the proposed approach, the scLBP method is compared with traditional texture descriptors such as LBP and CLBP.

Table III. Texture Classification Accuracy Comparison

Method	Accuracy
LBP	82%
CLBP	87%
scLBP	91%
proposed scLBP	94%

From the results, it can be observed that the proposed scLBP-based approach provides better classification accuracy compared with traditional LBP-based methods. This improvement is mainly due to the ability of scLBP to preserve and organize complex binary patterns that are ignored in conventional descriptors.

E. Discussion

The experimental results demonstrate that the proposed method effectively captures local texture structures and improves classification performance. By preserving consecutive binary transitions, the scLBP descriptor provides a richer representation of texture information.

Furthermore, the integration of machine learning classifiers allows the system to learn discriminative features more effectively. This combination leads to improved accuracy and robustness in texture classification tasks.

V. CONCLUSION

In this paper, a machine learning–based texture classification approach using Sorted Consecutive Local Binary Pattern (scLBP) features has been presented. The proposed method focuses on improving the representation of local texture patterns by preserving and organizing consecutive binary transitions that are often ignored in traditional Local Binary Pattern methods. By capturing richer local structural information, the scLBP descriptor provides a more effective representation of texture images.

The extracted scLBP features are converted into histogram-based feature vectors and used as input for machine learning classifiers to perform texture classification. Experimental analysis shows that the proposed approach achieves better classification accuracy when compared with conventional texture descriptors such as LBP and CLBP. The ability of scLBP to represent complex texture structures contributes to improved discrimination between different texture categories.

Although the proposed system demonstrates promising results, there are several opportunities for further improvement. In future work, deep learning techniques can be integrated with scLBP features to enhance feature learning and classification performance. In addition, multi-scale scLBP feature extraction can be explored to capture texture patterns at different spatial resolutions. The proposed method can also be extended to real-world applications such as medical image analysis, industrial surface inspection, and remote sensing image classification.

Overall, the results indicate that the scLBP-based framework provides an effective and reliable solution for texture classification and can serve as a foundation for further research in texture analysis and image processing.

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