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Texture Classification Using Deep Convolutional Neural Networks

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Abstract: ***Texture classification is an essential task in computer vision and image processing, commonly applied in areas like image recognition and remote sensing. Traditional methods such as Local Binary Pattern (LBP) have limitations in capturing complex texture features. This paper proposes the use of deep convolutional neural networks (CNNs) for texture classification, which can extract complicate texture details and significantly improve classification accuracy. Experimental results on the KTH - TIPS database confirm the superiority of the proposed CNN - based method over conventional LBP technique.***

Keywords: Texture Classification, Local Binary Pattern, Deep Learning, Confusion Matrix

1. Introduction

A basic visual feature that defines how materials appear in both natural and artificial settings is texture. It is essential for classifying objects and analyzing visual environments. Texture classification is important in computer vision applications like medical image analysis, recognizing patterns, object recognition, and surface defect detection. For texture analysis, basic techniques like the Local Binary Pattern (LBP) have been frequently used. However, LBP techniques have difficulty in capturing complex textures, particularly when dealing with variations in rotation, light, and scale. Basic texture classification techniques include model - based approaches for representation, statistical techniques like Local Binary Patterns (LBP), structural approaches for pattern analysis, and recent deep learning techniques like Convolutional Neural Networks (CNNs).

The structural or statistical features of textures in an image are described by mathematical models in model - based texture classification systems. In order to differentiate between various textures, these methods try to capture characteristics including patterns, regularities, and variances. Common approaches include Fractal Models, which uses fractal geometry to describe textures with self - similar patterns at various scales, and Markov Random Fields (MRF), which describe textures as stochastic processes defined by spatial correlations between nearby pixels [1].

The Wavelet Transform is another well - known approach that breaks down textures into frequency components in order to analyze patterns at various resolutions. These techniques are robust for use in applications like medical imaging, material inspection, and remote sensing because they work especially well when the basic texture includes recognized and repeating features [2].

Structural - based techniques for texture classification focus on analyzing the arrangement of texture elements, often called "primitives, " such as lines, dots, or shapes [1]. These methods study how these elements are organized in terms of spacing, orientation, and repetition to distinguish different textures. For example, textures like brick walls or woven fabrics have clearly identifiable patterns formed by repeating elements. Structural approaches use tools like morphological analysis and edge detection to identify and describe these primitives. Another technique involves using structural models that describe textures at multiple levels of detail. These methods work well for textures with regular and clearly defined patterns but may struggle with highly irregular or random textures [1]. Structural - based techniques are often used in applications like fabric inspection, surface quality control, and architectural image analysis, where the arrangement of elements plays a key role in texture recognition.

Statistical - based techniques for texture classification analyze the distribution of pixel intensities and their relationships in an image to identify different textures. These methods focus on features like contrast, roughness, and uniformity. Common approaches include Gray Level Co - occurrence Matrices (GLCM), which measure how often pairs of pixel values occur at specific distances and angles, and Local Binary Patterns (LBP), which describe the texture by comparing each pixel to its neighbors [1]. Statistical techniques are simple and effective, making them widely used in fields like medical imaging and pattern recognition.

Deep learning - based techniques for texture classification use neural networks to learn features from texture images. Instead of manually defining features, these models learn patterns, edges, and textures directly from raw data through multiple layers of processing. Early layers of a CNN capture simple features like edges, while deeper layers identify more complex patterns and relationships. These techniques are highly effective because they can handle diverse and complex textures, even in challenging conditions like noise or varying lighting. Pretrained models like VGG, ResNet, or Efficient Net are often fine - tuned for texture classification tasks, saving time and improving accuracy. Deep learning approaches are widely used in areas like medical imaging, materials science, and remote sensing, where accurate texture recognition is essential. However, they require a large amount of data and computational resources for training.

In this paper, texture classification using CNN is proposed. The remaining part of the paper is organised as follows: The literature review on existing methods for texture classification is presented in section 2. Materials and methods for texture classification is presented in section 3.

Experimental procedure and results are discussed in section 4. Finally, concluding remarks are given in section 5.

2. Literature Review

Texture classification is important area in computer vision. In this section, some of the existing works on texture classification are presented as follows:

Fujieda et al. [2] introduced wavelet Convolutional Neural Networks (Wavelet CNNs) for texture classification. In order to capture better texture patterns, this technique combines spectrum analysis using wavelet transformations, in contrast to typical CNNs that just concentrate on spatial information. Both low - and high - frequency features are maintained by exchanging wavelet - based operations for conventional convolution and pooling layers. Comparing this method to traditional CNNs, it increases accuracy while drastically lowering the amount of trainable parameters, which makes training simpler and requires less memory. This model is more successful at complicated texture identification tasks since it also exhibits resilience against variations in scale and orientation.

Zhao et al. [3] proposed completed robust local binary pattern (CRLBP) for texture classification. In this work, center pixel local area is replaced by its average local gray level to improve the robustness against noise and illumination. To make CRLBP more stable and robust, they introduced α parameter. Experimental results were obtained from three databases shows CRLBP ($\alpha = 1$ & 8) values are insensitive to noise and obtained better texture classification accuracy.

Feng et al. [4] proposed dominant - completed local binary pattern (DCLBP) to improve the robustness against noise. By converting DCLBP_C, DCLBP_S and DCLBP_M features into joint distributions, good accuracy on texture classification was obtained.

Hu et al. [5] proposed an improved technique for classifying textures, a procedure that finds patterns in images. By introducing the Adaptively Binarizing Magnitude Vector (ABMV) technique, it improved the Local Binary Pattern (LBP) scheme. In order to analyze textures more accurately, the ABMV approach dynamically modifies the threshold. For improved feature extraction, it breaks up images into smaller sections, particularly in smooth or uneven areas. When compared to traditional techniques, experiments on a Outex, UIUC, CURet, XU_HR and ALOT texture databases showed how effective it is at providing improved classification accuracy and robustness.

Kylberg and Sintorn [6] proposed evaluation of noise robustness of various texture classification techniques based on Local Binary Patterns (LBP). Using six texture datasets, this work evaluates eight improved LBP versions, including Improved LBP, Local Ternary Patterns, and Fuzzy LBP, in addition to traditional approaches like co - occurrence matrices and Gabor filters. The results indicate that all approaches decrease at high noise levels, however certain variations (such as Improved Local Ternary Patterns) perform well at low noise levels. Also, Shift LBP, a novel fast LBP variation is shown. This study highlights the necessity for specific approaches by suggesting that strength to depend on the dataset and technique.

Dan et al. [7] proposed a texture classification technique known as Joint Local Binary Patterns with Weber - like responses (JLBPW). To improve texture description, JLBPW applies a Weber's law - based reaction for intensity variations and combines patterns from various scales. This technique focuses on patterns that occur frequently, which reduces computing complexity. According to experiments conducted on open - source texture datasets, JLBPW outperforms current techniques in terms of classification accuracy while remaining effective and robust to changes in illumination and rotation.

Zhu et al. [8] proposed deep learning model to classify texture images. In this work reflection enhancement, elastic transformation and other data augmentation techniques were used to enhance and expand texture images. This method achieves a good accuracy which is better than traditional texture image classification methods.

Guo et al. [9] proposed completed local binary pattern (CLBP) scheme for texture classification. Three operators, viz., CLBP_C, CLBP_S, and CLBP_M, were considered to extract the features. The combination of these operators was achieved better texture classification accuracy compared to LBP.

Yaun [10] proposed a novel method for texture classification using Local Binary Patterns (LBP). Traditional LBP focuses only on first - order directional derivatives, losing valuable high - order information. The proposed method introduces a Derivative Local Binary Pattern (DLBP) that encodes both first - and higher - order derivatives. By incorporating circular shift sub - uniform patterns and scale space techniques, this approach achieved invariance to rotation and scale, making it robust for texture analysis. This process involves generating multiple histograms for different derivative orders and combining them for classification. Experiments conducted on various texture datasets, including rotated and scaled textures, show that the proposed DLBP performs better than existing methods in accuracy.

Krishnan and Vanathi [11] proposed a texture classification method combining Discrete Wavelet Transform (DWT) and LBP techniques. Texture classification involves identifying patterns, such as coarseness or smoothness, in images. Traditional methods using DWT or LBP separately had limitations in accuracy, especially with poor - quality images. In the proposed approach, input images are first decomposed into four sub - bands (LL, LH, HL, HH) using DWT. LBP features are then extracted from each sub - band, combined into a 1024 - feature descriptor, and classified using a k - Nearest Neighbors (k - NN) algorithm. The results show that the combined method improves accuracy and reduces computational complexity compared to existing techniques. It also performs well in noisy environments, demonstrating its robustness.

Simon and Uma [12] proposed Convolutional Neural Networks (CNN) to automatically extract features from texture images and combined with a Support Vector Machine (SVM) for classification. Traditional methods relied on manually designed features, but CNNs learn features automatically, offering better accuracy. This work highlights the advantages of combining deep learning features with traditional classifiers like SVM for robust and efficient image analysis, creating the way for applications in industrial inspection and defect detection.

Rachdi et. al [13] introduced the Multi - scale Ternary and Septenary Pattern (MTSP) for texture classification. It enhanced the Local Binary Pattern (LBP) approach by combining Single - scale Ternary and Septenary Patterns (STP and SSP) using set theory. Unlike traditional methods, MTSP extracts both local and global texture information with higher precision, making it robust to changes in scale, rotation, and illumination. MTSP is computationally efficient and performs well across diverse texture classification challenges. This study highlights MTSP's potential as a strong candidate for various texture analysis applications.

Hegenbart and Uhl [14] proposed an improved texture classification by extending Local Binary Patterns (LBP) to handle image scaling and rotation more effectively. It introduces a Scale - and Orientation - Adaptive LBP (SOA - LBP), which adjusts to changes in scale and orientation by estimating global image properties like scale and orientation. SOA - LBP uses a multi - resolution approach to create robust texture features across various scenarios. Tests on multiple datasets show SOA - LBP performed better than traditional methods, especially when textures vary in scale or orientation. This method is reliable for natural textures and noisy images but demands more computational power compared to simpler approaches. Overall, SOA - LBP offers a strong balance between accuracy and adaptability for complex texture classification tasks.

In spite of above existing methods, still it is interesting and challenging to develop novel texture classification methods for texture classification. In this direction, a novel approach for texture classification using CNN is proposed in this work.

3. Materials and Methods

In this section, Local Binary Pattern which is popular texture descriptor and proposed method using deep learning are discussed.

a) Local Binary Pattern:

Local Binary Patterns (LBP) is a popular descriptor to obtain the characteristics of the textures in the images. It was successfully in various application areas, face recognition, content-based image retrieval, and texture recognition. The advantage of this operator is that it is simple to calculate and robust against illumination. LBP operator, introduced by Ojala et al. [15] was used to describe image textures. It considers each pixel in an image and compares its intensity value with the intensity values of its neighboring pixels. For each pixel in the image, a binary code is generated by thresholding the neighboring pixel intensities with respect to the center pixel's intensity.

The output value of the LBP operator can be obtained as follows:

LBP $=\Sigma_{n=0}^{7} S\ (i_n - i_c)\ 2^n$

where i_c= center pixel value

i_n= neighbor pixel value

In Local Binary Pattern (LBP), the s (z) function typically represents a mapping from the binary pattern to a decimal value. Example for calculation in Local Binary Pattern is shown in Figure 1.

3	7	2
8	4	1
2	3	5

i_0	i_1	i_2
i_7	i_c	i_3
i_6	i_5	i_4

0	1	0
1		0
0	0	1

Figure 1: Example for calculation in LocalBinary Pattern

$= 0x2^0 + 1x2^1 + 0x2^2+0x2^3+1x2^4+0x2^5+0x2^6+1x2^7$

$=0 + 2 + 0+ 0+ 16+ 0 + 0 + 128$

=146 (LBP code generated)

b) Proposed model using deep learning:

Deep learning in texture classification identifies and categorizes patterns in images. Textures are the visible characteristics of surfaces, such as the metal's smoothness or the wood's roughness. Traditional approaches depended on manually created features, such Local Binary Patterns (LBP), which needed experts to create certain texture analysis procedures. Convolutional Neural Networks (CNNs) especially allows deep learning to automatically extract these features from data. CNNs process images layer by layer, recognizing complex patterns, edges, and forms before eventually differentiating between various textures. This method is capable of handling complex and different information; it is more accurate and flexible than traditional methods. The proposed model for texture classification using CNN is shown in Figure 2. A brief description about proposed model is presented below.

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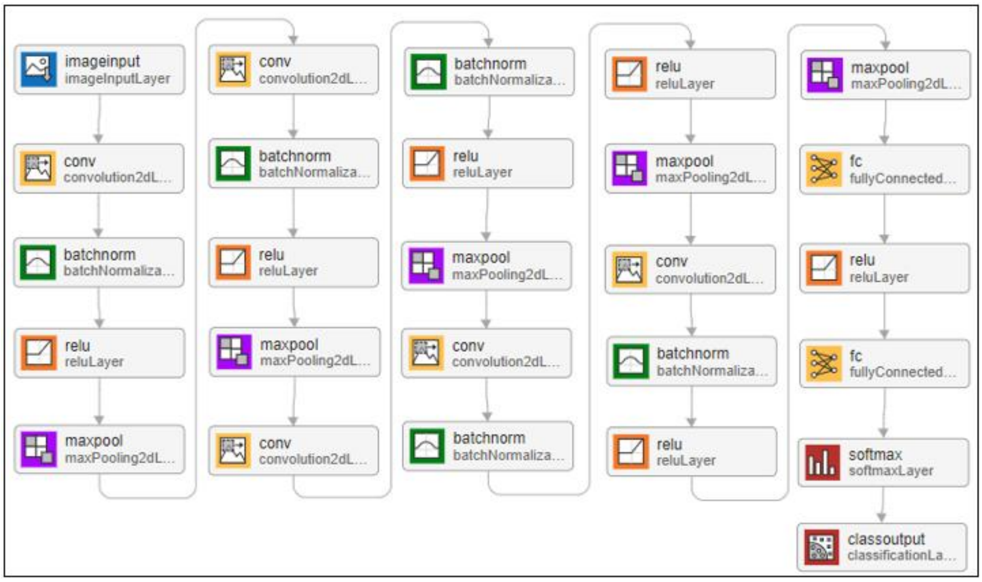

Figure 2: Block diagram of Proposed Convolution Neural Network Model

Image Input Layer: The network architecture starts with an image input layer that normalizes the 2D images, standardizing them for consistent processing.

Convolutional layer: It is the fundamental building block of deep learning model to extract features from image by using different kernels.

Batch normalization layer: This layer helps in improving the performance of model.

ReLU Layer: It is a nonlinear activation that keeps all negative values to zero.

Max pooling layer: This layer helps in reducing the dimensions of feature maps.

Fully connected layer: It is an interconnected neural network primarily used for classification purpose.
Further, in order to improve generalization, data augmentation techniques like random rotations and horizontal flips are applied, expanding the training dataset with varied perspectives and helping the CNN adapt to different transformations. This CNN architecture effectively utilizes deep learning's strengths, providing a robust framework for accurate texture classification. The parameters of the proposed CNN model like number of filters, stride, pooling, learning rate, etc. are presented in experimental procedure and results section.

4. Experimental Procedure and Results

In this section, a brief description about texture database, performance metrics, and results are discussed.

a) Database:
The experiments were conducted on the KTH - TIPS database [16], which contains 81 images per class for 10 different material categories. This database is widely used for evaluating texture classification models. KTH - TIPS (Textures under Varying Illumination, Pose, and Scale) database is a widely used benchmark in texture classification research. It was designed to test the robustness of texture recognition models under challenging real - world conditions by providing images with variations in illumination and scale. The dataset includes 10 different texture classes, such as wool and bread etc., each representing materials. Within each class, there are images taken from multiple samples of the same material to introduce intra - class variability. These samples are captured under various lighting conditions and at different scales to reflect the complexity and diversity of natural textures. Due to these controlled variations, KTH - TIPS has become a valuable resource for evaluating texture classification models' ability to generalize across changes in environmental factors. Images were pre - processed and divided into training and testing sets to assess model performance. A few samples from this database are shown in Figure 3.

Figure 3: Few sample images of Texture from KTH - TIPS database

b) Performance Metrics:

The performance of the proposed CNN model is evaluated using accuracy and confusion matrix. These performance metrics are defined as follows:

- Accuracy: The percentage of correctly classified images over the total number of images.
- Confusion Matrix: This helps to know the performance of the model against each class. Usually, diagonal elements represent correctly classified classes and off diagonal elements represent misclassified classes.

c) Results

In experimentation, the performance of the traditional Local Binary Pattern (LBP) method is compared with the proposed Convolutional Neural Network (CNN) architecture.10 - fold cross validation approach is considered for experimentation. In this approach, dataset is divided into 10 folds, then 9 folds are used for training and remaining one is used for testing. This procedure is repeated for each fold and the average of all accuracies is considered as final accuracy. Initially, LBP method is applied on KTH - TIPS database image to extract texture features. Then, these features are applied to kNN classifier for classification. The LBP method achieved a classification accuracy of 96.5%. Further, the confusion matrix is also calculated to know performance on each class and it is shown in Figure 4.

Later, the proposed CNN architecture is applied on same database. In this architecture, the parameters are chosen as follows: image input layer input size [256 256 3], convolution layer filter size 6, number of filters 32, padding, same, max pooling layer pool size 2, stride 2, fully connected layer output size 128, further convolution layers parameters changed to filter size 5 and 12, number of filters 64, 8 and 128 also. learning rate of 0.01, L2 regularization factor 0.0005, mini - batch size 32 and Validation frequency 10.

The result of proposed CNN model is shown Figure 5. It is observed that the proposed model achieved an accuracy of 99.1% which outperform over conventional LBP.

Confusion matrix using CNN model is calculated to analyze the classification performance across the 10 texture categories and it is shown in Figure 6. It is observed that the CNN model shows significant improvements over LBP, particularly in distinguishing between complex textures with subtle variations.

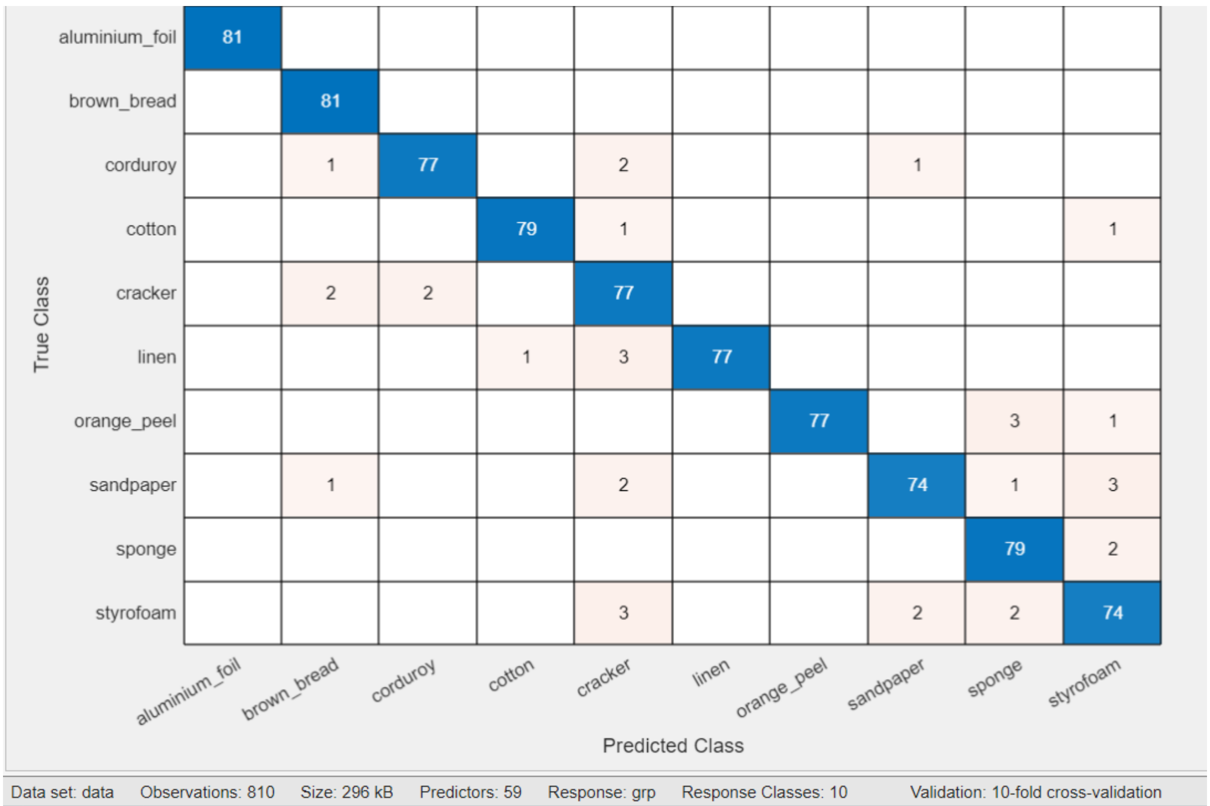

Figure 4: Confusion Matrix using Local Binary Pattern

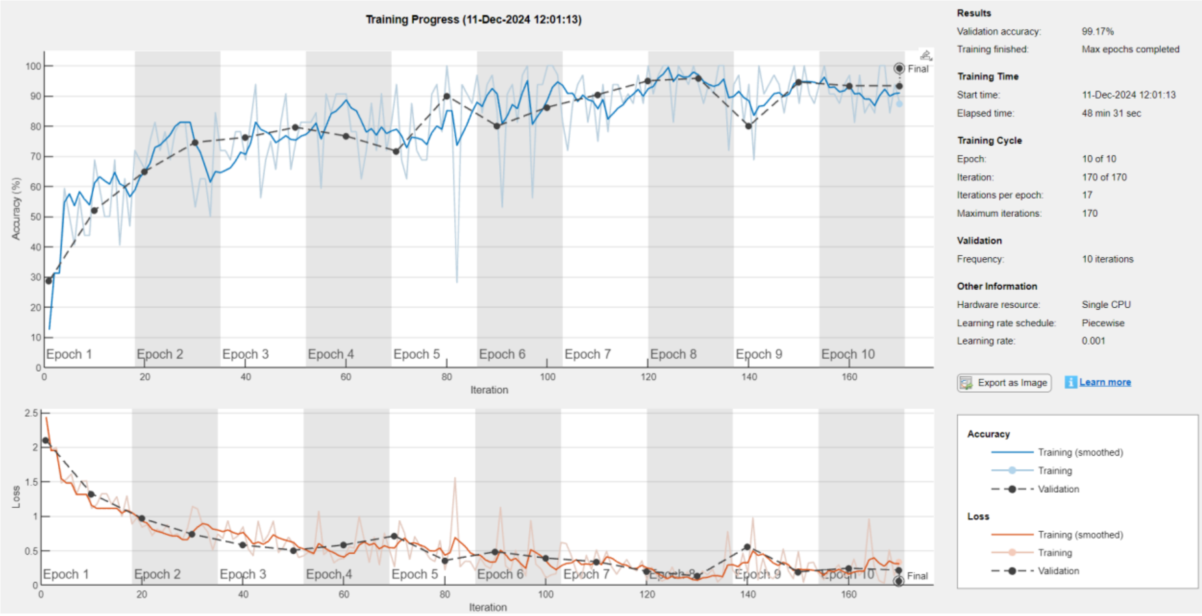

Figure 5: Accuracy using CNN model

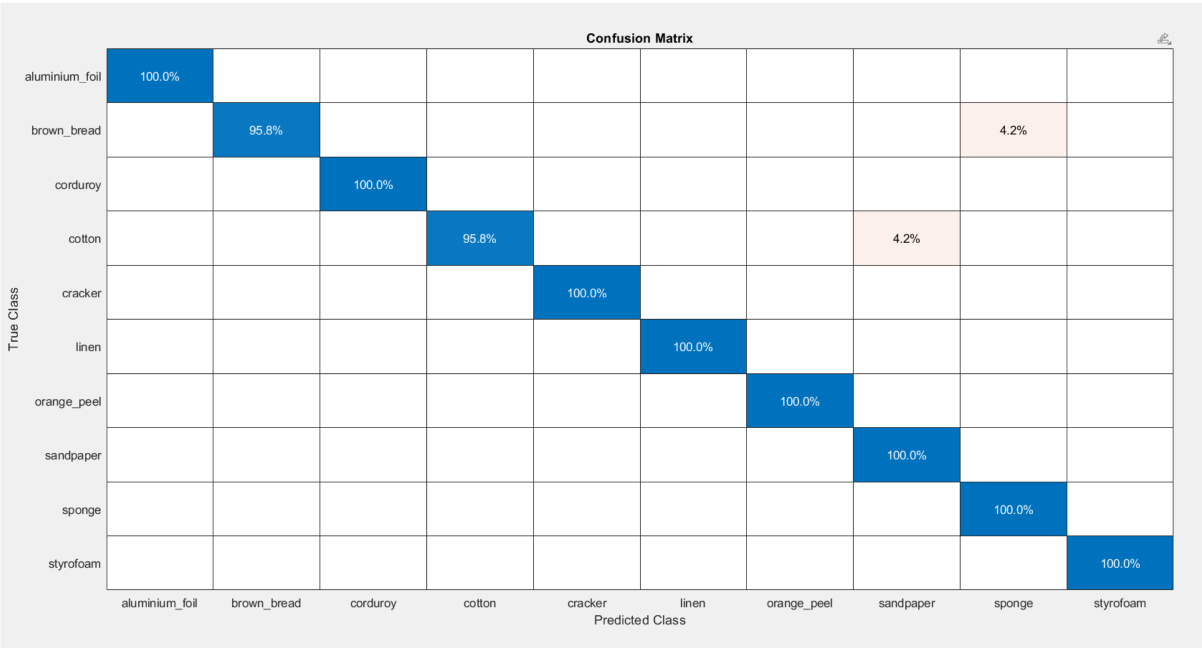

Figure 6: Confusion matrix using proposed CNN model.

5. Conclusion

The experimental results demonstrate that deep learning models, specifically CNNs, outperform over traditional texture classification methods such as LBP. The proposed CNN model achieved higher classification accuracy, confirming its ability to capture complex texture details. Experimentation on the KTH - TIPS database show that the CNN model with the ReLU activation function is achieved the best performance with 99.1% accuracy. Future work could explore new deeper network architectures or hybrid models combining traditional methods with CNNs to further enhance texture classification accuracy.

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