



DeepFake Detection Improvement for Images Based on a Proposed Method for Local Binary Pattern of the Multiple-Channel Color Space

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Abstract: DeepFake is a concern for celebrities and everyone because it is simple to create. DeepFake images, especially high-quality ones, are difficult to detect using people, local descriptors, and current approaches. On the other hand, video manipulation detection is more accessible than an image, which many state-of-the-art systems offer. Moreover, the detection of video manipulation depends entirely on its detection through images. Many worked on DeepFake detection in images, but they had complex mathematical calculations in preprocessing steps, and many limitations, including that the face must be in front, the eyes have to be open, and the mouth should be open with the appearance of teeth, etc. Also, the accuracy of their counterfeit detection in all previous studies was less than what this paper achieved, especially with the benchmark Flickr faces high-quality dataset (FFHQ). This study proposed, a new, simple, but powerful method called image Re-representation by combining the local binary pattern of multiple-channel (IR-CLBP-MC) color space as an image re-representation technique improved DeepFake detection accuracy. The IR-CLBP-MC is produced using the fundamental concept of the multiple-channel of the local binary pattern (MCLBP), an extension of the original LBP. The primary distinction is that in our method, the LBP decimal value is calculated in each local patch channel, merging them to re-represent the image and producing a new image with three color channels. A pretrained convolutional neural network (CNN) was utilized to extract the deep textural features from twelve sets of a dataset of IR-CLBP-MC images made from different color spaces: RGB, XYZ, HLS, HSV, YCbCr, and LAB. Other than that, the experimental results by applying the overlap and non-overlap techniques showed that the first technique was better with the IR-CLBP-MC, and the YCbCr image color space is the most accurate when used with the model and for both datasets. Extensive experimentation is done, and the high accuracy obtained are 99.4% in the FFHQ and 99.8% in the CelebFaces Attributes dataset (Celeb-A).

Keywords: Deep learning, DeepFake detection, Digital image forensics, Image re-representation, Convolutional neural network CNN, DenseNet121.

1. Introduction

DeepFake is a fake face image generated by one of the five facial manipulation techniques entire face synthesis, identity swap, attribute manipulation, expression swap, and miscellaneous [1] These methods concern celebrities and anyone around the globe because the tools and applications to create them are easy to utilize and available. DeepFake uses machine learning (ML) and artificial intelligence (AI) to make deceptive videos and images. Correspondingly, deep learning techniques like

autoencoders and generative adversarial networks (GANs) were used to create fake faces that are difficult to expose by humans, even by software [2].

GANs [3] have dramatically improved the realism of high-quality face photos, such as PGGAN [4], StyleGAN [5], etc. Note that this study used a digital manipulation type generated by StyleGAN because it produces impressive results, such as high-resolution facial images with an extremely high level of realism [6]. The StyleGAN unsupervised training procedure produced photos with variations in hair, freckles, and other features. Additionally, it makes the image's artificial controls possible.

Various DeepFake detection approaches and strategies have recently been presented to counter blackmail and defamation. Many methods have been proposed to detect DeepFake, including using pre-trained models like Xception, InceptionNet, EfficientNet, etc., because of their ability to extract manipulation features, such as [6-8] etc. Others started constructing their own CNN models, such as [9-11], etc., to work on a specific feature. In this research, the pre-trained model DenseNet121 [12] was used to extract the features map, followed by Dense layers to identify fake ness.

On the other hand, texture analysis research was used in pattern recognition and computer vision to detect fraudulent images. The local binary pattern (LBP) technique [13] was adopted as a texture description because it is invariant to monotonic illumination changes, is straightforward to implement, and has low computational complexity and solid discriminative power [14]. Most texture classification approaches in this field used grayscale photos, ignoring color, a critical perceptual signal. Note that a color picture has three channels. Using several information channels can help increase the discriminability of retrieved features, which have not been adequately studied [14]. The MCLBP [14], a natural extension of the LBP algorithm, was one of the best color texture representation and classification methods. MCLBP uses single-channel texture features and multi-channel color information to show channel correlations and dependencies. Using color information to extract image texture has research value. This vital issue is our research focus in this paper as well.

So far as we know, there have not been any methods for detecting and analyzing fake images based on making new image re-representations based on MCLBP. This research proposes a novel approach, image re-representation by combined local binary pattern in multi-channel color space (IR-CLBP-MC). IR-CLBP-MC is an image with three color channels made by combining the three LBP values from the original color image's three color channels. With pre-trained CNN, this method was used for image deep-fake detection. Meanwhile, this approach combined local feature-based detection with deep feature-based detection methods. The local feature method is more reliable than other methods because it takes information from all parts of the face, and the information it gives is not visible [15]. The deep feature method is similar to the local feature method but uses a deeper filter to pull out more complex features, which currently has the highest level of accuracy [15]. The contributions and innovations of this paper are:

- 1) Each pixel's inner-channel and inter-channel characteristics are encoded using a multiple-channel (cross-channel) LBP. This MCLBP description extracts three channels' local features and textures simultaneously, exposing dependencies and linkages.
- 2) Applied the LBP to extract texture characteristics from a single channel and composite color texture features from many channels by merging the LBP pixel from a single channel with the other from multi-channels; to produce IR-CLBP-MC.
- 3) Applied the IR-CLBP-MC on the different color space images with two techniques, overlap and non-overlap, to show this approach's ability with CNNs to detect the fake faces.
- 4) Evaluated IR-CLBP-MC on two benchmark datasets to demonstrate the proposed representation descriptor image's effectiveness, efficiency, and correctness.

The rest of this paper is arranged as follows. Section 2 explains the theoretical background of this paper. Section 3 introduces related works. Section 4 displays the research methodology in detail. Section 5 covers the experimental setup. Section 6 reports the experimental results and discussion. Finally, Section 7 concludes this paper and points out possible future work.

2. LBP and MCLBP

The central concept of the proposed method in this paper comes from the LBP and MCLBP methods, as described in this section.

2.1 LBP

The LBP operator is often used to get localized spatial characteristics for texture analysis, image detection, and pattern recognition. LBP, a popular texture feature extraction method, should help detect fake faces [10]. In [13] they were presented LBP as a useful texture pattern descriptor for describing an image's local texture patterns. It is commonly utilized in image-processing-related applications. The LBP uses a block size of 3×3 pixels, with the center pixel serving as a threshold for nearby pixels and the LBP code for a center pixel being formed by converting the computed threshold value to a decimal value. The mathematical expression of LBP [16] is given as follows:

$$\text{LBP} = \sum_{i=0}^{P-1} s(n_i - G_c)2^i \quad (1)$$

$$s(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases}$$

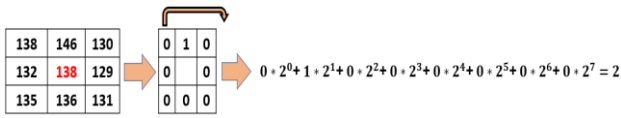


Figure. 1 Example of computing LBP for a test 3×3×1 image block

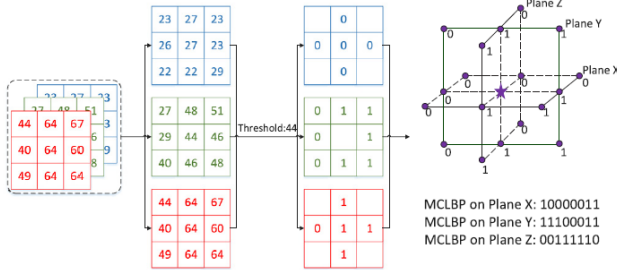


Fig. 2 MCLBP construction process in R-G-B sequence: (a) A local patch of a color image, (b) In R-G-B channel sequence, the center value (44) of G channel is taken as the threshold. Similarly, in G-B-R sequence the threshold is 27 in B channel and in B-R-G order the threshold is 64 in R channel, (c) Binarization results of (b) and (d) illustration of the corresponding positions of the binarized neighborhood values in the local patch and the MCLBP codes in the three orthogonal planes [14]

Where P denotes the number of nearby pixels, n_i is the i th neighboring pixel, and c is the center pixel. The acquired LBP code extracts the histogram features of size 2^P . As a result, the histogram feature vector length for eight nearby pixels is 256. Fig. 1 shows the LBP procedure with a G_c value of 138 and eight surrounding pixels.

This study used the default clockwise way of picking neighbors, which affected the LBP texture. Also, the central concept of the LBP approach continues with finding a histogram to represent the texture image of the LBP values. Regardless, this paper is satisfied with finding the LBP decimal value of each pixel for later use in re-representing the image to produce a new image.

2.2 MCLBP

The multiple channels of LBP (MCLBP) is proposed by [14], as a natural extension and refinement of the LBP algorithm for extracting and representing the color textures of each color channel in the original color image, cross-channel feature information is also considered as well. They were taken RGB as an example of their method that briefly illustrate as follows:

Firstly, they take a local $3 \times 3 \times 3$ cube from the image see Fig. 2 (a), and then split the local cube into three channels separately, as shown in Fig. 2 (b). Taking the center point in the G-channel as the

threshold to the 18 neighborhood points; then the binarization operation is performed on the three orthogonal planes of the local cube, as listed in Fig. 2(c). The three orthogonal planes are termed as plane X, plane Y, and plane Z, as presented in Fig. 2 (d). These three local features make up their MCLBP descriptor [14], which is defined as follows:

$$MCLBP_{F,R,P}(i, j) = \sum_{n=1}^P s_F(r_n - r_c)2^{n-1} \quad (2)$$

$$s_F(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

Where $f = 1, 2, 3$. Here, for convenience of description, they combined the multiple channels and the single channel for calculating easily. In Eq. (2), f denotes the index of the three orthogonal planes ($f = 1: X, 2: Y, 3: Z$). For example, the binary serial number of plane X is 10000011 and the corresponding LBP value is 131.

Secondly, for a color texture image, they count the MCLBP histograms as in the original LBP method.

The proposed method in this search is based on the same concept of the MCLBP method, but after splitting the local cube into three channels separately. we deal with each channel's block alone by taking the center point in it as the threshold to calculate the LBP decimal value and then combining them to produce a new image, see Subsection (4.1.4).

However, our proposed method combines the main idea of the MCLBP method, which says that the LBP features of three color channels of a color image should be utilized; With, the LBP decimal value is assigned to each local patch channel by applying Eq. (1). Lastly, our proposed idea comes by merging the three LBP values of the three channels (first channel, second channel, and third channel) to re-represent the image and produce a new image with three color channels. The produced image takes care of the parts of the LBP pattern that are important for each pixel in the color image.

3. Related works

Researchers recently developed various ways to address DeepFake detection in images. This section will discuss the relevant studies according to the types of detection methods. They are *deep learning features*, *face-warping features*, *visual features*, and *machine learning features* [17].

The first type is *deep learning detection methods*, which depend on the CNNs models to classify the DeepFake images. For instance, in the study [2], they used the FisherFace algorithm with the LBP histogram (FF-LBPH) to extract features, then

utilized the restricted boltzmann machine (RBM) as a learning rule and the deep belief network (DBN) to detect the DeepFake. Their results show that the LBPH-based feature extraction combined with the deep learning technique helped find the fake face image. Likewise, the study [10] looked at the LBP texture features to show that the textures of fake faces are very different from those of real faces by proposing a way to spot fake faces. They came up with a new CNN called LBP-Net. Its architecture was based on ResNet and Gram-Net, which work to find fake faces using information about their global texture features and augmentation techniques. Some utilized deep learning in feature extraction and DeepFake detection, such as the authors in this research [7], who also employed the augmentation technique with deep learning feature extraction depending on a pre-trained model like EfficientNetB4, then used a few layers such as Dense and Dropout with LSTM to detect the fake faces. Similarly, the paper [8] used six pre-trained models to detect DeepFake in images. Their results showed that the DenseNet121 model was better than the others in DeepFake detection. Also, the Fake Detection Fine-tuning Network (FDFtNet) approach [11] used pre-trained models as a backbone to their networks, such as SqueezeNet, ShallowNetV3, ResNetV2, and Xception with augmentation techniques, to achieve a good result on the Celeb-A dataset. On the other hand, using transform-based feature extraction with CNNs showed promising results, such as when the authors [18] proposed a new model to find synthetic images based on the wavelet-packet representation.

Indeed, in the previous studies, some of them involved complex mathematical calculations, especially those that used histograms and augmentation techniques. Also, some of them work on global features, which means they don't pay attention to how pixels are placed in local textures that focus on each part of an image.

The *face warping artifacts detection methods* is another type, that all most of them employed CNNs to detect the presence of such artifacts from the fake face image and the surrounding areas. In paper [6], They proposed a novel attention-based layer and inserted it in the Xception Net model architecture to improve classification performance and their ability to indicate the manipulated facial regions. This attention map worked as a mask to remove any irrelevant features from the high-dimensional features within the network.

The *visual artifacts detection methods* are fake detectors based on simple visual aspects such as eye color, missing reflections, missing details in the teeth areas, etc. In the study [9], after determining the face,

they relied on the facial landmarks as a feature extraction to select the eye area and used Mask R-CNN to segment out the iris regions. Then they detected the consistency between the corneal specular highlights of the two eyes by designing a residual attention network (RAN). This type of DeepFake detection method has many limitations, including that the face must be in front, the eyes have to be open, and the mouth should be open, etc.

The last type of DeepFake detection in this literature is *machine learning methods*, some of which are based on statistical computation as feature extraction. In research [19], they proposed utilizing the expectation maximization (EM) algorithm with naive classifiers like SVM and KNN to detect fake faces in more than one database to show the effectiveness of this method.

However, the accuracy of their counterfeit detection in all previous studies were less than what this paper achieved, especially with the benchmarks FFHQ.

4. Research methodology

In this work, many phases were used in the proposed framework, see Fig. 3. This section explains all these phases in detail, as below:

4.1 Preprocessing phase

Before the DeepFake image can be classified, it needs to be preprocessed, which improves the image for further processing. In this study, preprocessing was done in more than one step. Here are the steps that make up this phase:

4.1.1. Detect and crop the face

Face detection happens after an image is read from the dataset [20], and its generation is performed using the deep MediaPipe technique. Note that MediaPipe face detection is a super-fast solution to detect face features, and it comes with six landmarks and multi-face support[21]. It depends on BlazeFace [22], a lightweight and well-performing face detector fitted for mobile GPU inference. The face detection library alone is insufficient because some pictures have more than one face. Hence, the box attribute was used. To determine whether the face is clear and represents the concerned face in the picture. Lastly, the Box attribute was used to crop the person's face from the image.

4.1.2. Conversion of images to other color spaces

The RGB color space is not the only one that can be used to analyze the colors of pixels in a color space,

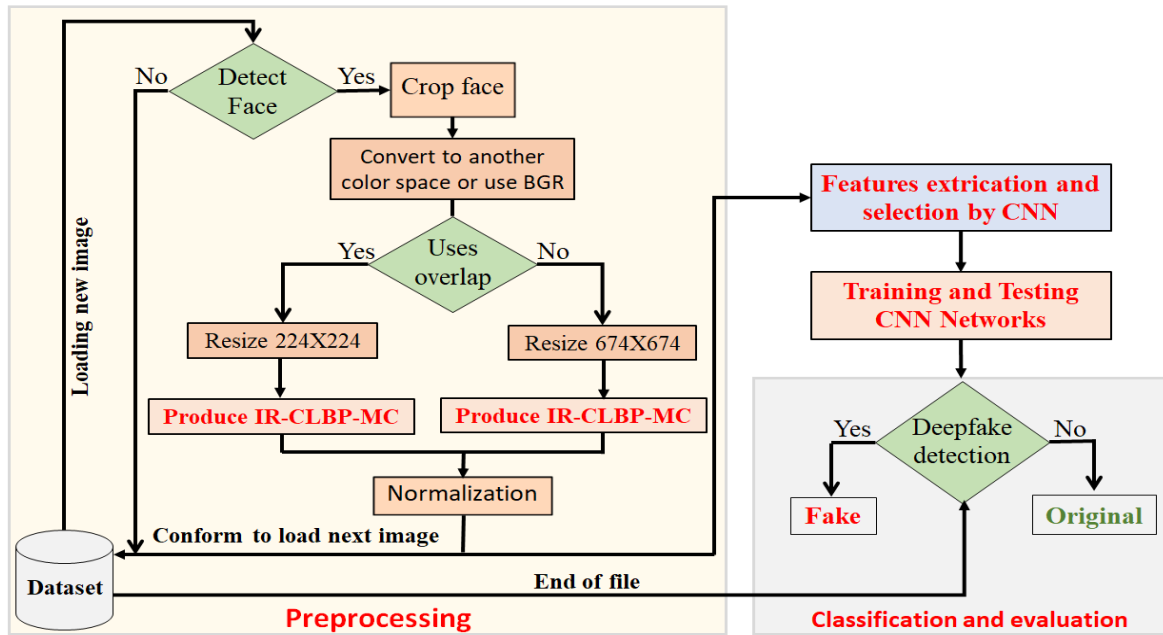


Figure. 3 Illustrating the phases of the research framework

as there are numerous color spaces available for representing the hues of the pixels [23-25].

Only the three-color spaces from the four main families that were most frequently used were used in this work and discussed in this section, as shown below:

A) The trichromatic theory says that any color may be matched by combining the three main hues. Therefore, they were separated into device-dependent RGB and device-independent XYZ virtual main spaces, whose primaries are not real.

B) "Luminance" represents achromatic information, and "chrominance" measures chromatic information. Only the first two subfamilies were used: YCbCr, which divides chrominance and luminance signals for television transmissions, and LAB, which provides a metric to establish a relationship between a color difference observed by a human observer and a distance measured in the color space.

C) Perceptual spaces measure subjective human color perception using intensity, hue, and saturation. The hue-luminance-saturation (HLS) double hexcone model and the hue-saturation-value (HSV) hexcone model are evaluated directly from primary spaces.

Using the (IR-CLBP-MC) method with the overlap and non-overlap techniques on each of these six types of color spaces images, we got twelve new image re-representations.

4.1.3. Resizing image

All of the photos in the datasets utilized in this study, Flickr face high quality (FFHQ), 1 million fake faces (1MFF), and Celeb attribute (Celeb-A),

were 1024×1024 pixels in size. However, when the face was cropped out of the picture, an image with a size of about 600×700 pixels was obtained. Therefore, the input image must be 224×224 in size, per the pre-trained model DenseNet121[12] utilized as our model's input layer. In addition, two resize procedures were employed because this work's suggested strategy used the overlap and non-overlap techniques to produce the IR-CLBP-MC image (for more information on the IR-CLBP-MC approach, see Subsection 4.1.4).

The first one resizes the image to 672×672 to ensure that the output image, from the proposed method, will be the right size for the input layer. This is because the non-overlap technique was used with a block size of 3×3; see Fig. 3 preprocessing step, which means that the output image will be a third of the size of the original image. Subsequently, the second one was to change the size of the image to 224×224 because the overlap method was utilized. Because of this, the final image will be the same size as the image sent to the IR-CLBP-MC method.

4.1.4. Proposed approach (IR-CLBP-MC)

The proposed approach in this paper is image re-representation by combined local binary pattern in multi-channel color space (IR-CLBP-MC). IR-CLBP-MC uses color texture and intensity information by creating a new image with three channels from each original patch's color channels. On the other hand, MCLBP is a natural extension and refinement of the LBP algorithm for representing and classifying color textures with multiple color

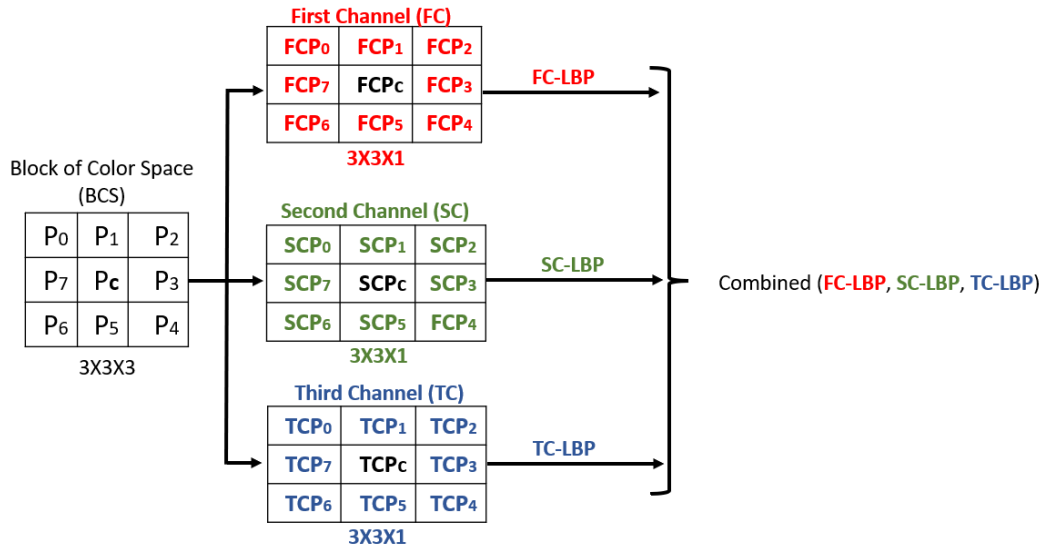


Figure. 4 Flowchart of the proposed approach (IR-CLBP-MC)

channels and features in a single color channel [14]; it was adapted in this study (see section 2). Fig. 4 depicts the proposed IR-CLBP-MC technique.

After reading an image and converting it to another color space (like RGB, XYZ, HLS, HSV, YCbCr, and LAB) or using BGR as it is read, using the proposed method and according to its following steps:

A) Select a block of color space (BCS) from an image with 3×3 size to eight neighbor pixels containing three color channels; see Fig. 5 (a) as an example.

B) Separate each channel alone, namely, First Channel (FC), Second Channel (SC), and Third Channel (TC), respectively, and determine the center pixel as a threshold; see Fig. 5 (b) as an example. Which separate each channel's (R, G, and B) block alone and detect the center points (138, 135, and 119) from each of them, respectively.

C) Calculate the LBP of each channel, namely, FC-LBP, SC-LBP, and TC-LBP, respectively; see Fig. 5 (c) as an example, binarization results of (B), and calculate the LBP of each channel to find the relevant decimal value.

D) Merge the three LBP values (FC-LBP, SC-LBP, and TC-LBP) to produce a new pixel; see Fig. 4 (d) as an example, to combine the three decimal values results of (C), to produce a new pixel of the representative image.

Algorithm 1 illustrates the steps of this approach. After utilizing this method on each 3×3 local patch from left to right and top to bottom, the image was represented by combining the LBP of Multiple-channels (IR-CLBP-MC). Hence, this color features or color texture picture (IR-CLBP-MC) can be utilized as a three-channel image with color and texture information.

Image (IR-CLBP-MC) has three channels. Each channel contains color and intensity data from the original color space image, distinguishing it from LBP image descriptors. Compared to past studies, the math employed was simple and few. With this strategy, our main objective was to create a new image re-representation based on LBP from the color information and intensity information of a color space image with three channels that could be used with a powerful technique called CNN as it is well-known that performs better when dealing with images with three channels [26].

Algorithm 1: Construction of IR-CLBP-MC

<p>Input: Preprocessing image detected face and cropped face with the size of $W \times H$</p> <p>Output: IR-CLBP-MC image by overlap technique</p> <p>00: Img = Load preprocessing image (BGR type)</p> <p>01: Img = Convert Img to another color space // Optional step</p> <p>02: Resize Img to 224 X 224</p> <p>03: For $i=1$ to 223 do // Image width</p> <p>04: For $j=1$ to 223 do // Image height</p> <p>05: BCS= Select block of Img[i,j] // $3 \times 3 \times 3$ local cube</p> <p>06: FC, SC, TC= Separate each block channel from BCS//$3 \times 3 \times 1$ cube for each channel</p> <p>07: FC-LBP, SC-LBP, TC-LBP= Calculate LBP values of FC, SC, TC// Use Equ. 1 to find LBP value</p> <p>08: IR-CLBP-MC[i,j]= Combine (FC-LBP, SC-LBP, TC-LBP) // Marge three LBP values</p> <p>09: End for</p> <p>10: End for</p> <p>11: Return IR-CLBP-MC</p>

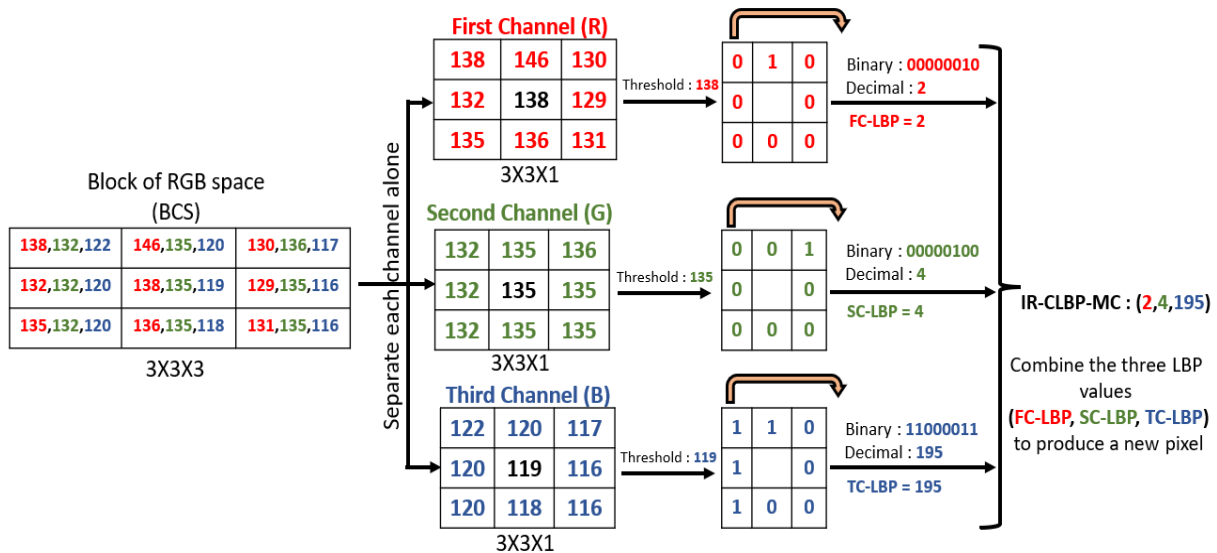


Figure. 5 Example to explain the steps of the proposed approach (IR-CLBP-MC) when using an RGB image

4.1.5. Normalization

The image that comes out of the IR-CLBP-MC is a color textual representation of the color space image fed into it. Like any color image, it has three channels, each pixel in them with a value between 0 and 255. As with any image, the IR-CLBP-MC image needs to use normalization to make its pixel values stand out more. Note that the deep learning network also works with numbers between 0 and 1 [2].

4.2 Extract feature and classification

This section will explain the CNNs method that was used in the feature extraction and selection phase with the classification phase, as follow:

4.2.1. Feature selection and extraction using CNN

CNNs are one of the best ways to understand the content of an image[27, 28], and they have done a great job at tasks like image segmentation, classification, detection, and retrieval [29, 30]. Using CNNs for the imagenet large scale visual recognition challenge (ILSVRC) [31] is crucial to come out of deep learning. These CNNs that have already been trained have learned to describe a wide range of images in detail [32]. Hence, this paper uses DenseNet121 as an input layer to pull out the deep embedding texture features from the IR-CLBP-MC image made by the proposed method in this research.

4.2.2. Classifier

A few layers were utilized as classifiers to investigate and determine whether the image was

fake or not after extracting the feature map from entering IR-CLBP-MC into our model. The Dense layers used LeakyReLU activation functions; the other layers are Flatten, Dropout, and Batchnormalization. Given that the DeepFake detection problem is a binary classification problem, the output layer's final layer featured a single node with Sigmoid activation functions. Additionally, binary cross entropy was employed as the loss function, and the the-normal value was used as the kernel initializer. Consequently, Adam[33] was employed as an optimizer.

5. Experimental setup

The experiment was run on a ZBook HP Intel Core (TM) i7-7500U @ 2.70GHz 2.90GHz, VGA AMD 2GB, and RAM 24GB with Windows 10. Python was applied for the suggested method's face detection and cropping. Keras from Tensorflow was utilized to deploy and build the pre-trained CNN (DenseNet121). For further details on this paper's model, read Subsection (4.2.2). The proposed model was assessed using a subset of 6k photos for training and 2k images for testing from each of our two benchmarks. All benchmarks in this study employed 50 epochs and 128 batch sizes for training, with 75% training and 25% validation. To make a fair comparison between the six types of color space worked on with the suggested approach, the test data (2k photos, 1k real, and 1k fake) in all databases utilized was isolated in a distinct folder. Hence, the model did not view it during training.

Table 1. Comparison of the proposed method testing results from different color spaces in terms of **A**: accuracy (%) and **L**: loss

Benchmark	Method	IR-CLBP-MC					
		RGB	XYZ	HLS	HSV	YCbCr	LAB
FFHQ-1MFF	Overlap	A : 93.8 L : 0.98	A : 91.6 L : 1.03	A : 92.6 L : 0.95	A : 95.0 L : 0.82	A : 99.4 L : 0.52	A : 95.4 L : 0.66
	Non-Overlap	A : 90.1 L : 1.09	A : 86.7 L : 1.28	A : 89.9 L : 1.26	A : 89.9 L : 1.01	A : 93.3 L : 0.87	A : 90.7 L : 1.05
Celeb-A-F-SyCA	Overlap	A : 98.9 L : 0.35	A : 98.8 L : 0.22	A : 99.0 L : 0.35	A : 99.6 L : 0.19	A : 99.8 L : 0.14	A : 99.4 L : 0.24
	Non-Overlap	A : 98.2 L : 0.21	A : 98.0 L : 0.22	A : 98.8 L : 0.2	A : 99.0 L : 0.11	A : 99.6 L : 0.21	A : 99.2 L : 0.11

6. Experiment results and discussion

This section presents the benchmarks that used in this study and the discovered results with discussion as follows:

6.1 Dataset description

Most of the datasets for DeepFake research are videos, and the few available image datasets are either too small or of low quality. Hence, for this study, more than one dataset was chosen after making sure it was of good enough quality and had enough images. Here's a brief description of each one:

Flickr face high quality (FFHQ) [5]: a 70k real faces dataset that includes 70,000 PNG high-quality images was retrieved from Flickr by Nvidia for their StyleGAN paper and was utilized as authentic images.

CelebFaces attributes (Celeb-A) [34]: large-scale data collection containing 200k JPG high-quality images was used as authentic.

1 million fake faces (1MFF) [5]: this is a fake image created using Nvidia StyleGAN comprising JPG high-quality images.

Diverse fake face dataset (DFFD) [6]: this is a fake image created using the pre-trained model of StyleGAN to produce 100k high-quality pictures from the Celeb-A dataset; we will call it F-SyCA. The DFFD dataset includes other types of fake images, but only this one was used because this paper focuses on entire face synthesis.

After downloading the datasets, we put each set of images into its folder. Subsequently, 8k pictures (4k real and 4k fake) were picked randomly from FFHQ-1MFF and 8k images from Celeb-A-F-SyCA datasets to be used as a standard for judging how well the proposed method works.

6.2 Comparative evaluation of the IR-CLBP-MC results

To evaluate, the suggested method of Image Representation by Combined the local binary pattern of multiple-channel (IR-CLBP-MC) in this study was applied to two datasets and several types of color spaces using overlap and non-overlap techniques. The observed results were as follows:

First of all, if you look at the results of each technique with each type of color space, you can see that the texture is a little bit different; see Fig. 6, (c), and (d). This difference was confirmed after training and testing the same model with all types and on all databases. In addition, the overlap technique demonstrated that the used model worked better with the IR-CLBP-MC, see Table 1.

Second, compared to the outcomes of earlier researchers, using the non-overlap technique in all datasets and for some types of space color like HSV, YCbCr, and LAB is pretty decent. Additionally, this technique substantially reduces high-quality photographs' dimensions to a third of their original size. This was when high-quality images had dimensions of more than 600 pixels. Other than that, the significant components of its color and intensity information were also extracted. We have accomplished this using high-quality photos from the FFHQ, 1MFF, and Celeb-A databases.

Third, the test results showed that the YCbCr image color space is the most accurate when used with the model and all the databases, and this is in line with what researchers had found in the past when they employed this type of color space to find fake images [14, 35, 24].

6.3 Compartmented and analysis of the histogram of the IR-CLBP-MC results

The histogram diagrams Fig. 7 illustrates the original face image histogram from Fig. 6 (a), with two color space type histograms which give higher

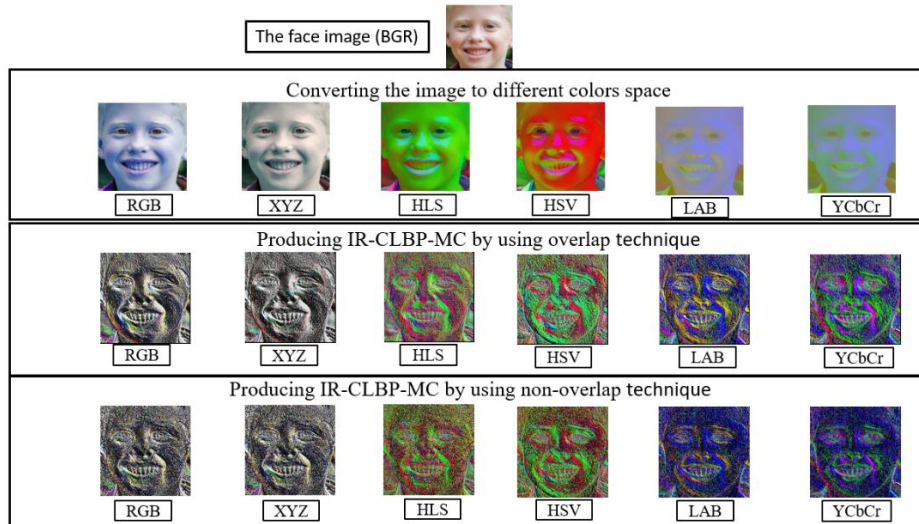


Figure. 6 Examples of visuals IR-CLBP-MC by applying the proposed method with overlap and non-overlap techniques on different color space images: (a) The image after detecting and cropping the face from the original image BGR, (b) Converting the face image to a different kind of color space images, (c) Producing IR-CLBP-MC for each color space image by applying our proposed approach with overlap technique, and (d) Producing IR-CLBP-MC for each color space image by applying our proposed approach with non-overlap technique

and lower accuracy of DeepFake detection in the FFHQ-1MFF benchmark dataset; and its IR-CLBP-MC histogram produced from these color space types. (Fig. 6 (b), (c), and (d), YCbCr, as well as XYZ).

In histogram Fig. 7 (a), you can see that the color values of the pixels in the original face image range from 0 to 255. When you compare (b) and (c) to (a) in Fig. 7, you can see that (a) and (c) are similar. In the three channels, it can be observed that the number of pixels is limited to high color values from 140 to about 150. There is a small difference between them in the number of pixels, which is early less in (c), and the high chromatic values are different in the three channels. The fact that both domains (BGR and XYZ) belong to the same family of color space explains why these two histograms look similar, see Subsection 4.1.2. Moreover, when you compare (b) to (a) and (c), you can easily see the difference because the highest number of pixels in the second and third channels is in the middle of the range of color values, especially between 100 and 170 except for the first channel, which has color values from 0 to 255.

The way this color space type is spread out can be considered a characteristic of this type of image, which has been done well in most studies before and in this paper. The histograms in Fig. 7 (d), (e), (f), and (g) demonstrate, in general, how well the suggested method re-represents the image by redistributing the color values of the pixels in the three channels in a compatible and convergent way that includes all of the color values (0 - 255).

Additionally, most pixels have decreased their color values (intensity and contrast) in all three channels. Therefore, it looks like the number of pixels with lower color values is higher, which is the opposite of what the original image and color space types showed. Consequently, the overlap method makes it easy to see how the IR-CLBP-MC histograms for YCbCr and XYZ differ. In (d), the number of pixels seems to be spread close to the normal distribution. However, there is a small difference between the number of pixels in the three channels with the same color values. But in (e), the number of pixels seems to be spread out in a way that looks the opposite of a normal distribution. These differences between (d) to (a), (b), and (c), as well as between (d) and (e), can explain the performance of the same model used with all color space types, which was achieved better results with the YCbCr color space than with others. Note that the redistribution of the number of pixels that contain different and distinct color values for each of the three channels in the image produced by the suggested method can account for its good performance in all color kinds.

6.4 Comparison with state-of-the-art methods

The suggested method's detection accuracy was compared with nine state-of-the-art methods, some of which deployed the LBP with CNN for DeepFake detection [2, 10] and others used deep learning techniques to detect fake faces [6-8, 11]. Even though those who used transform based [18] or facial landmarks based [9], also depended on CNN to detect

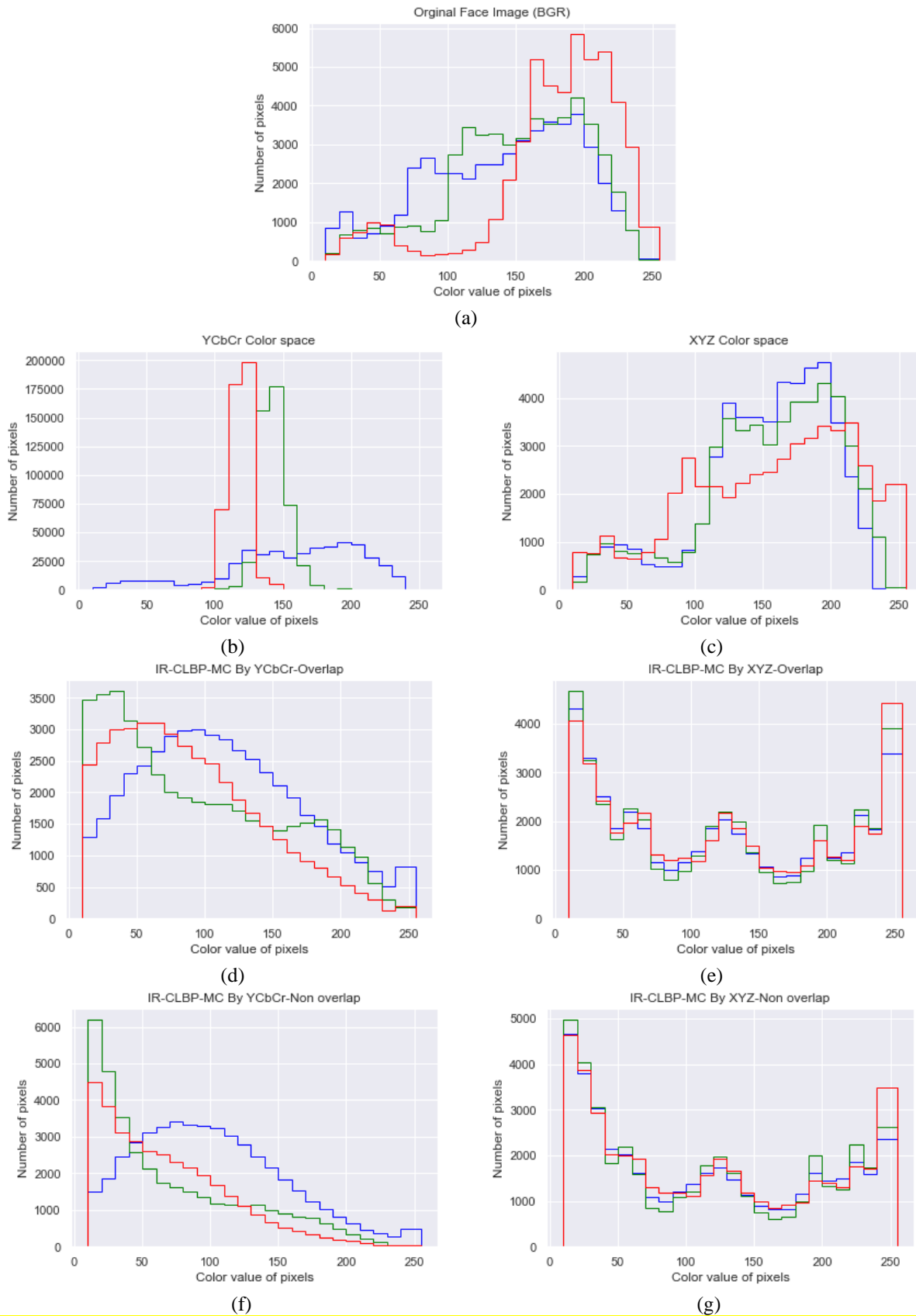


Figure. 7 Examples of histograms of the same image; the original face and the color space type with its IR-CLBP-MC; The three colors, **Blue**, **Green**, and **Red**, represented the number of three channel pixels in each image: First Channel, Second Channel, and Third Channel

Table 2. Comparisons of the suggested methods with state-of-the-art, **Fe. Ex. Me.:** Feature Extraction Method, **Dep. Det. Me.:** DeepFake Detection Methode, **Acc:** Accuracy.

Ref.	Fe. Ex. Me.	Dep. Det. Me.	Classifier	Dataset	Acc
[2]	LBP-Based	deep learning features	DBN with RBM	FFHQ	94.9%
				DFFD	97.8%
[10]	LBP-Based	deep learning features	LBP-Net	FFHQ-1MFF	98.7%
[7]	deep learning based	deep learning features	EifficientNetB4 + LSTM	FFHQ-1MFF	98%
[8]	deep learning based	deep learning features	DenseNet121	FFHQ	99%
[11]	deep learning based	deep learning features	FDFtNet	Celeb-A-PGGAN	90.29%
[18]	Transform based	deep learning features	Wavelet-Packet-CNN	Celeb-A-PGGAN	99.64%
				FFHQ -STYLEGAN	98.5%
[6]	deep learning based	face warping artifacts	XceptionNet + Attention layer	DFFD	99.69%
[9]	facial landmarks based	visual features	RAN	FFHQ-GAN	97%
[32]	statistic computation based	machine learning features	KNN	Celeb-A-GDWCT	88.4%
			KNN	Celeb-A-ATTGAN	92.6%
			SVM	Celeb-A-STARGAN	93.1%
			KNN	Celeb-A-STYLEGAN	99.6%
			SVM	Celeb-A-STYLEGAN2	99.8%
Ours	Image Re-representation based MCLBP	deep learning features	DenseNet121 + CNN	FFHQ-1MFF	99.4%
				DFFD	99.8%

manipulated images. Only one used ML [19] in this field.

These state-of-the-art algorithms were evaluated using FFHQ, 1MFF, Celeb-A, and DFFD datasets, in which these approaches' detection accuracies are from articles. Table 2 compares the suggested method's detection accuracies with state-of-the-art.

The results present the most significant detection accuracies with IR-CLBP-MC utilizing the overlap technique on YCbCr color space images for both benchmark datasets are 99.4% for FFHQ-1MFF and 99.8% for Celeb-A- F-SyCA. Since 99% [8]for FFHQ and 99.8% [19] for DFFD are the most outstanding detection accuracies reported, this comparison demonstrates that deep embedding color textural characteristics from IR-CLBP-MC of color space images beats state-of-the-art approaches. Furthermore, deep IR-CLBP-MC characteristics improve detection accuracy with no restrictions, such as the face being in front with both eyes open [9]. Also, some other studies go into finding histograms for more than one channel in a single image [2], or using an augmentation technique [10, 11], which means implementing many steps and using complicated math operations in a preprocess.

The LBPs are excellent texture descriptors that capture any textural anomalies in faked photos. Thus, collecting deep textural characteristics from IR-CLBP-MC of YcbCr improves detection accuracy. Subsequently, Subsection 4.1.4 of this research describes the proposed method. It reveals how simple

the math operations are and how easy it is to make a new image re-representation of color information and intensity information from a color space image by following a few steps. Therefore, we could say this method is more accessible than the others.

7. Conclusions and future works

This paper proposed a novel preprocessing method to create a new image re-representation that has been utilized with a pre-trained (CNN) to detect DeepFake successfully. In this work, the BGR image converted to different color space images are, RGB, XYZ, HLS, HSV, YCbCr, and LAB; and then produce the Image Re-representation by Combined the Local Binary Pattern of Multiple-Channel (IR-CLBP-MC) image from each of them using the overlap and non-overlap techniques. Other than that, the deep embedding features were extracted from IR-CLBP-MC using the DenseNet121 pretrained model. The proposed approach was evaluated on two benchmarks: DeepFake detection challenge and diverse fake face. Note that the proposed technique uses available information and contains complementary information, as proven by the increased performance of multiple-channels LBP over merging them in a new picture re-representation. Compared with state-of-the-art, overlap and non-overlap had good detection performance with various color space images as the overlap method is superior to the non-overlap method in all color spaces. The

YCbCr type achieved the best accuracy with both techniques and in all datasets.

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Author contributions

In this research article author contributions are as follows: "conceptualization, Nada Hussein M. Ali; methodology, Nada Hussein M. Ali; software, Mohammed Thajeel Abdullah; validation, Mohammed Thajeel Abdullah; formal analysis, Nada Hussein M. Ali; investigation, Mohammed Thajeel Abdullah; resources, Mohammed Thajeel Abdullah; data curation, Nada Hussein M. Ali; writing—original draft preparation, Mohammed Thajeel Abdullah; writing—review and editing, Mohammed Thajeel Abdullah; visualization, Mohammed Thajeel Abdullah; supervision, Nada Hussein M. Ali; project administration, Nada Hussein M. Ali; funding acquisition, Mohammed Thajeel Abdullah"

References

- [1] A. Malik, M. Kuribayashi, S. M. Abdullahi, and A. N. Khan, "DeepFake Detection for Human Face Images and Videos: A Survey", *IEEE Access, Institute of Electrical and Electronics Engineers Inc.*, Vol. 10. pp. 18757–18775, 2022.
- [2] S. T. Suganthi, M. U. A. Ayoobkhan, N. Bacanin, K. Venkatachalam, H. Štěpán, and T. Pavel, "Deep learning model for deep fake face recognition and detection", *PeerJ Comput Sci*, Vol. 8, 2022.
- [3] I. Goodfellow, J. P. Abadie, M. Mirza, B. Xu, D. D. W. Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial networks", *Commun ACM*, Vol. 63, No. 11, pp. 139–144, Oct. 2020.
- [4] T. Karras, T. Aila, S. Laine, and J. Lehtinen, "Progressive Growing of GANs for Improved Quality, Stability, and Variation", *arXiv preprint arXiv*, Oct. 2017.
- [5] T. Karras, S. Laine, and T. Aila, "A Style-Based Generator Architecture for Generative Adversarial Networks", In: *Proc. of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 4401-4410, 2019.
- [6] H. Dang, F. Liu, J. Stehouwer, X. Liu, and A. Jain, "On the Detection of Digital Face Manipulation", In: *Proc. of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 5781-5790, 2020.
- [7] A. Agnihotri, "DeepFake Detection using Deep Neural Networks", *PhD diss., Dublin, National College of Ireland*, 2021.
- [8] H. S. Shad, M. Rizvee, N. T. Roza, S. M. Hoq, M. M. Khan, A. Singh, A. Zaguia, and S. Bourouis, "Comparative Analysis of Deepfake Image Detection Method Using Convolutional Neural Network", *Computational Intelligence and Neuroscience*, Vol. 2021.
- [9] H. Guo, S. Hu, X. Wang, M. C. Chang, and S. Lyu, "Robust Attentive Deep Neural Network for Exposing GAN-generated Faces", *IEEE Access*, Vol. 10, pp. 32574-32583, 2022.
- [10] Y. Wang, V. Zarghami, and S. Cui, "FAKE FACE DETECTION USING LOCAL BINARY PATTERN AND ENSEMBLE MODELING", In: *Proc. of International Conference on Image Processing, ICIP*, Vol. 2021, pp. 3917–3921, Sep. 2021.
- [11] H. Jeon, Y. Bang, and S. S. Woo, "FDFtNet: Facing Off Fake Images using Fake Detection Fine-tuning Network", In: *Proc. of ICT Systems Security and Privacy Protection: 35th IFIP TC 11 International Conference, SEC 2020, Maribor, Slovenia, September 21–23, 2020, Proceedings 35*, pp. 416-430, 2020.
- [12] G. Huang, Z. Liu, L. V. D. Maaten, and K. Q. Weinberger, "Densely Connected Convolutional Networks", In: *Proc. of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 4700-4708, 2017.
- [13] T. Ojala, M. Pietikainen, and D. Harwood, "A COMPARATIVE STUDY OF TEXTURE MEASURES WITH CLASSIFICATION BASED ON FEATURE DISTRIBUTIONS", *Pattern Recognition*, Vol. 29, No. 1 pp. 51-59, 1996.
- [14] X. Shu, Z. Song, J. Shi, S. Huang, and X. J. Wu, "Multiple channels local binary pattern for color texture representation and classification", *Signal Process Image Commun*, Vol. 98, Oct. 2021.
- [15] K. N. Ramadhani and R. Munir, "A Comparative Study of Deepfake Video Detection Method", In: *Proc. of 2020 3rd International Conference on Information and Communications Technology, ICOIACT 2020*, pp. 394–399, 2020.
- [16] M. S. Karis, N. R. A. Razif, N. M. Ali, M. A. Rosli, M. S. M. Aras, and M. M. Ghazaly, "Local Binary Pattern (LBP) with application to variant object detection: A survey and method", In: *Proc. 2016 IEEE 12th International Colloquium on Signal Processing and Its Applications, CSPA 2016*, 2016.
- [17] R. Tolosana, S. R. Tapiador, R. V. Rodriguez, E. G. Sosa, and J. Fierrez, "DeepFakes detection

- across generations: Analysis of facial regions, fusion, and performance evaluation”, *Engineering Applications of Artificial Intelligence*, Vol. 110, Apr. 2022.
- [18] M. Wolter, F. Blanke, C. T. Hoyt, and J. Garcke, “Wavelet-Packet Powered Deepfake Image Detection”, *arXiv Preprint arXiv:2106.09369*, 2021.
- [19] L. Guarnera, O. Giudice, and S. Battiato, “DeepFake Detection by Analyzing Convolutional Traces”, In: *Proc. of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, pp. 666-667, 2020.
- [20] H. K. Dhahir and N. H. Salman, “A Review on Face Detection Based on Convolution Neural Network Techniques”, *Iraqi Journal of Science*, Vol. 63, No. 4, pp. 1823–1835, 2022.
- [21] C. Lugaresi, J. Tang, H. Nash, C. McClanahan, E. Uboweja, M. Hays, F. Zhang, C. Chang, M. G. Yong, J. Lee, W. Chang, W. Hua, M. Georg, and M. Grundmann, “MediaPipe: A Framework for Building Perception Pipelines”, *arXiv Preprint arXiv:1906.08172*, 2019.
- [22] Y. Kartynnik, A. Ablavatski, I. Grishchenko, and M. Grundmann, “Real-time Facial Surface Geometry from Monocular Video on Mobile GPUs”, *arXiv Preprint arXiv:1907.06724*, 2019.
- [23] N. Vandenbroucke, L. Busin, and L. Macaire, “Unsupervised color-image segmentation by multicolor space iterative pixel classification”, *Journal of Electronic Imaging*, Vol. 24, No. 2, p. 023032, 2015.
- [24] A. Porebski and V. T. Hoang, “Multi-color space local binary pattern-based feature selection for texture classification”, *Journal of Electronic Imaging*, Vol. 27, No. 1, p. 011010, 2018.
- [25] A. F. H. Sewan and M. S. M. Altaei, “Copy Move Forgery Detection Using Forensic Images”, *Iraqi Journal of Science*, pp. 3167–3181, Sep. 2021.
- [26] L. Nanni, S. Ghidoni, and S. Brahnam, “Handcrafted vs. non-handcrafted features for computer vision classification”, *Pattern Recognit*, Vol. 71, pp. 158–172, Nov. 2017.
- [27] M. T. Abdullah, W. L. A. Yaseen, and Q. A. Abed, “Convolutional Neural Networks Based Optimal Management of Agricultural Crops”, *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, Vol. 12, No. 11, 401-410, 2021.
- [28] M. R. Oraibi and A. M. Radhi, “Enhancement Digital Forensic Approach for Inter-Frame Video Forgery Detection Using a Deep Learning Technique”, *Iraqi Journal of Science*, Vol. 63, No. 6, pp. 2686–2701, 2022.
- [29] A. Khan, A. Sohail, U. Zahoora, and A. S. Qureshi, “A survey of the recent architectures of deep convolutional neural networks”, *Artificial Intelligence Review*, Vol. 53, No. 8, pp. 5455–5516, Dec. 2020.
- [30] A. S. A. Alzhra and M. S. H. A. Tamimi, “Image Compression Using Deep Learning: Methods and Techniques”, *Iraqi Journal of Science*, pp. 1299–1312, Mar. 2022.
- [31] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, A. C. Berg, and L. F. Fei, “ImageNet Large Scale Visual Recognition Challenge”, *International Journal of Computer Vision*, Vol. 115, 211-252, 2015.
- [32] K. R. Revi and M. Wilsy, “Image forgery detection using deep textural features from local binary pattern map”, In *Journal of Intelligent and Fuzzy Systems*, Vol. 38, No. 5, pp. 6391–6401, 2020.
- [33] D. P. Kingma and J. Ba, “Adam: A Method for Stochastic Optimization”, *arXiv Preprint arXiv:1412.6980*, 2014.
- [34] Z. Liu, P. Luo, X. Wang, and X. Tang, “Deep Learning Face Attributes in the Wild *”, In: *Proc. of the IEEE International Conference on Computer Vision*, pp. 3730-3738. 2015.
- [35] J. Y. Choi, Y. M. Ro, and K. N. Plataniotis, “Color local texture features for color face recognition”, *IEEE Transactions on Image Processing*, Vol. 21, No. 3, pp. 1366–1380, Mar. 2012.