A fake face detection system using a hybrid discrete Chebyshev wavelet transform and a convolutional neural network.

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ABSTRACT

The widespread use of artificial intelligence has led to the exploitation of this development in the development of manipulation processes, for example, face manipulation with deep learning, which poses a great danger and threat to information safety and digital security. This work proposes a new hybrid system in which a new filter extracted from discrete Chebyshev wavelet transform (DChWT) $\omega_{r,s}(t)$is effectively integrated with an artificial convolutional neural network and employed in the process of detecting face forgeries. The capabilities and characteristics of the proposed waves were utilized, namely the orthogonality property and the multi-precision analysis property of waves in the spatial frequency domain in spatial learning in artificial convolutional networks. The performance of the proposed system in this work stands out in the superior performance of the Face Forensics standard, with the achievement of 99.98% accuracy with a recall value of 99.89%, and 99.91% precision. The confusion matrix, developed after comprehensive analysis, serves to evaluate the classification performance of a dataset containing both real and fake datasets. This evaluation aims to achieve system efficiency by identifying the hybrid system's strengths in detecting diverse manipulation techniques and challenges. In this study, the hybrid system outperformed modern methods by 2.3% in AUC-ROC, achieving high computational efficiency within the required timeframe and maintaining this efficiency.

1. Introduction

The emergence and spread of competitive convolutional neural networks (CNNs) has led to the ability to create highly sophisticated artificial faces that are difficult for humans to distinguish from real ones. This deepfake technology is used to obscure the truth, commit fraud, and spread misinformation. Consequently, there is a pressing need for an automated and effective system to combat facial identity theft. While traditional detection techniques exist in deep learning based on convolutional neural networks (CNNs), they rely on spatial features that are difficult to counter with modern manipulation techniques and the distortions that occur during compression [1].

The techniques previously used to overcome forgery in 2018 include Face2Face technology in forensic analysis, which is considered a traditional method due to the damage caused to images and videos by compression, resulting in data loss with 95% accuracy in deepfakes [2]. Face detection with the GAN-ResNet hybrid model achieves 83% accuracy and 0.825AUC for detecting fake faces [3]. Fake faces

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were detected using an artificial neural network with a Fourier transform accuracy of 57%, after achieving 77% accuracy with the ResNet18 model [4]. Fake video detection with the enhanced GNN-CNN dual-stream network achieved 99.3% accuracy using various fusion strategies [5]. Face detection was improved with a convolutional neural network (CNN) using a Gaussian filter and a high-frequency component after initial processing using a GAN [6]. The transformations were combined with a convolutional neural network to identify faces and recognize facial features after removing noise and compression accurately 90%, in addition to working with GoogleNet [7-9] without using wavelet transformations. Facial emotions were recognized in [10], [11] with an artificial convolutional neural network with wavelet transformations accurately 90%- 99%, in addition to other work with deep learning also to accurately identify people [12], [13]. All of these works did not distinguished from real faces and fake ones.

2. Methodology

2.1. Wavelet transform

The family formed from microwaves through stretching and contracting processes in the parent waves depends on the operators s and r in Equation 1 [12].

$$\omega_{r,s}(t) = |r|^{\frac{1}{2}}\omega\left(\frac{t-s}{r}\right) \qquad r,s \in R \quad r \neq 0$$

$where \qquad \omega(t) = [\omega_0(t), \omega_1(t), \ldots, \omega_{M-1}(t)]^T$

The basis $\omega_0(t), \omega_1(t), \ldots, \omega_{M-1}(t)$ are orthogonal on the [0, 1]

Using Equation 1 and performing the transformation to obtain one-dimensional Chebyshev waveforms in Equation 2,

$$\omega_{u,v}(t) = \begin{cases} \frac{c_u 2^{\frac{m}{2}}}{\sqrt{\pi}}\omega_u(2^{m+1}t - 2v + 1) & \frac{v-1}{2^m} \leq t < \frac{v}{2^m} \\ 0 & o.w \end{cases} \qquad (2)$$

$$where\ c_u = \begin{cases} \sqrt{2} & u = 0 \\ 2 & u = 1,2,\ldots \end{cases}$$

where: the resolution level $m = 1,2,\ldots.$ $v = 1,2,\ldots 2^m$ is a translation parameter, and $u = 0,1,2,\ldots, M-1$ the polynomial order

Any function within f(t) ∈ L²[0,1] can be expanded due to the orthogonal projection property in equation 3

$$f(t) = \sum_{v=1}^{\infty}\sum_{u=0}^{\infty} A_{u,v}\omega_{u,v}(t) \qquad (3)$$

where $\quad A_{u,v} = \langle f(t), \omega_{u,v}(t)\rangle_{w_v}$

the weight function $w_v(t) = w(2^{\{m+1\}}t - 2v + 1)$ from the inner product.

2.2. Preprocessing

The two-dimensional image extension I(x,y) will utilize new two-dimensional wavelets

$$\omega_{u_x,v_x,u_y,v_y}(x,y) = \omega_{u_x,v_x}(x) \cdot \omega_{u_y,v_y}(y) \qquad (4)$$

Finding the fundamental filter for the proposed waves from equation 2 using the nucleus in the equation, with the parameters for the wave filter being (m), which is called the kernel range and represents the filter size $\frac{v-1}{2^m} \leq t < \frac{v}{2^m}$, translation parameter v represents the spatial location, u and c_u

In the image analysis process with new waves, the coefficients are separated into two types: the low-frequency approximation coefficients (LL) and the horizontal, vertical, and diagonal detail coefficients

(LH, HL, HH), respectively. Through the convergence property that characterizes new wavelets as in Theorem 1,

Theorem 1: for an image I(x,y) with bounded second partial derivatives $\left|\frac{\partial'' I}{\partial x''}\right| \leq N$ and $\left|\frac{\partial'' I}{\partial y''}\right| \leq N$, the discrete Chebyshev wavelet transform expansion converges uniformly with coefficient bound:

$$\left|A_{u,v}\right| < \frac{N\sqrt{2\pi}}{2u^{5/2}(m+1`)(m+3)(m^2-1)} = \left(\sigma\left(u^{-4}v^{-5/2}\right)\right) \qquad (5)$$

The approach theory ensures that high-frequency image distortions and manipulations can be detected using wavelength parameters because they are so small.

2.2.1. Dataset

The dataset used for FaceForensics++ contains 1.8 million and 1,000 images. Deepfake and Face2Face processing techniques were applied, utilizing face spoofing and swapping through data compression and high compression methods. The dataset is divided into 270 training videos, 140 verification videos, and 140 test videos.

2.3. Deep learning architecture with DCHWT-CNN

The deep network is enhanced with the proposed wavelength synthesis technique, which combines discrete Chebyshev wave transformations with a synthetic convolution network to form a new network. This network comprises two key components: the micro wavelength flow and the feature extraction unit. After applying three-level wavelength analysis, the focus is on the LH, HL, and HH bands, which are susceptible to falsification. The spatial flow is achieved through three RGB channels with convolutional layers to detect spatial distortions.

2.3.1. Classification and Merging Process

The characteristic dynamics of microwaves are counterbalanced by the spatial characteristics imparted by the EfficientNet-B4 deep learning network, resulting in a binary classification that reflects truth or deception with a total parameter count of 19.3 million at 23 ms/image.

The dataset sources are input and analyzed, then compressed by the proposed model and convoluted by the new network. The deep learning process then classifies the input faces, as illustrated in Figure 1 shows the input to represent the face image for initial processing with the new filter and illustrates the feature map and work stages.

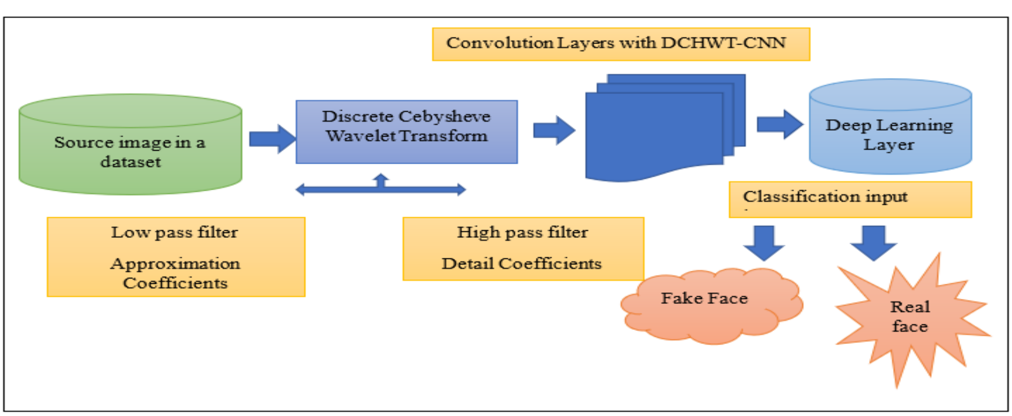

Fig. 1. Methodology Diagram: DCHWT-CNN Hybrid System for Fake Face Detection

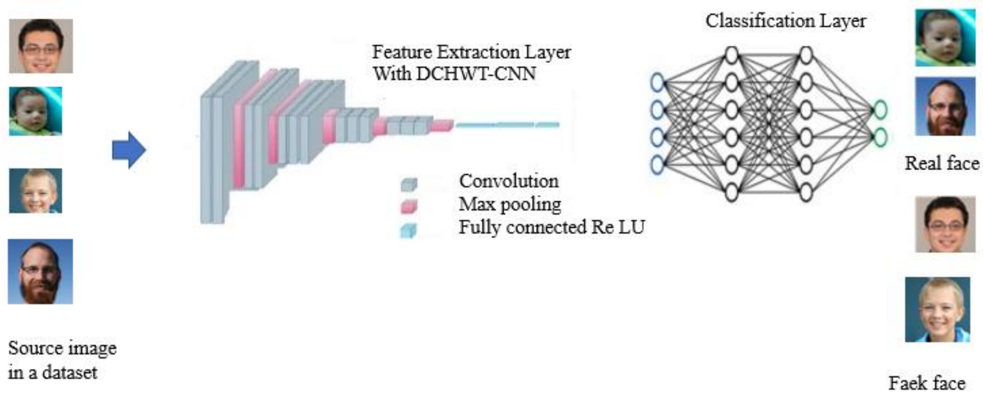

Fig. 2. Representation of face detection and classification as fake or real using deep learning and hybrid approaches :DCHWT-CNN

3. Results and Discussion

3.1. Hybrid System Evaluation

The results and accuracy obtained in this work validate the proposed hybrid approach to classification using the FaceForensics++ dataset, with 270 videos (70% of the data) trained, 140 videos (15% of the data) verified, and 140 videos (15% of the data) tested in a deep learning process. The exceptional performance of the proposed system is exemplified by its 99.98% accuracy in classifying real and fake faces, demonstrating the system's effectiveness in medical applications such as forensics. The system's precision in classifying fake faces (99.91%) represents a significant advantage in security applications for reducing manipulation, false accusations, and fraudulent activity. The 99.89% recall and sensitivity rate, representing the system's efficiency and ability to detect genuine and fake faces in all images and videos within the dataset, along with a very low error rate of 0.11%, is crucial in cybersecurity because the proposed system detects deepfake images, which pose significant security risks. The F1-Score ratio, representing the harmonic mean, measures 99.9%, maintaining exceptionally balanced performance. The system demonstrated a 2.3% improvement in AUC-ROC compared to traditional methods, reaching 0.99, which allows for an assessment of the system's performance with the dataset.

3.2. Efficiency of the Confusion Matrix

The confusion matrix exhibits excellent diagnostic properties:
The excellent diagnostic features revealed by the confusion matrix are as follows:
Real faces representing correct positives = 9990
Fake faces representing false positives = 99990
Incorrect diagnoses are divided into positives and negatives as follows: incorrectly classifying real faces as fakes and incorrectly classifying fake faces as real, with a value of 9 for both cases.
The high accuracy rate of predictions (99.98%) demonstrates the system's efficiency in counteracting distortions and falsifications under various pressure and manipulation techniques. The symmetrical distribution of errors shows the negative and positive rates, demonstrating the system's ability to achieve balance and challenge in detecting deepfakes from training data, thus challenging various types of manipulation.

The conclusive results for classifying real or fake faces using the confusion matrix provide a detailed analysis of how the proposed system performs. The accuracy obtained is based on the correct and incorrect results for classifying faces, using the positive results (TP and FP) for real faces and the negative results (FN and TN) for fake faces, As in the following relationships and figure 3 represents the accuracy values obtained in the confusion matrix

$$\text{accuracy} = \frac{(\text{TP}+\text{TN})}{(\text{TP}+\text{TN}+\text{FP}+\text{FN})} = 99.9836\%$$

$$\text{Precision} = \frac{\text{TP}}{(\text{TP}+\text{FP})} = 99.91\%$$

$$\text{Recall/Sensitivity} = \frac{\text{TP}}{(\text{TP}+\text{FN})} = 99.89\%$$

$$\text{Specificity} = \frac{\text{TN}}{(\text{TN}+\text{FP})} = 99.90\%$$

$$\text{F}_1 - \text{Score: } 2 \times \frac{(\text{Precision}\times\text{Recall})}{(\text{Precision}+\text{Recall})} = 0.99$$

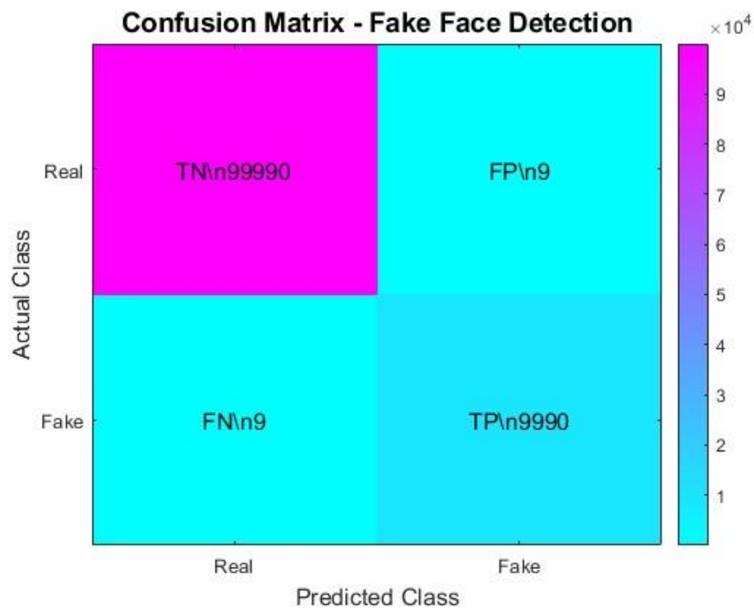

Fig. 3. Confusion matrix

3.3. Comparison of Work with Previous Work

The results obtained indicate the superiority of the DChWT-CNN hybrid model over the methods mentioned in the Introduction section. The previous methods, using a convolutional neural network with ResNet18, achieved 77% accuracy [4], while the proposed system achieved 99.98% accuracy. The [6] method, with an improved Gaussian filter, achieved 90% accuracy, a significant improvement of 22.98%, which is considerably lower than the efficiency achieved by our system.

The GAN-ResNet hybrid system achieved an accuracy of 83% with an AUC of 0.825 [3], demonstrating the superiority of the system DChWT-CNN in accuracy. In [5], the GNN-CNN network achieved an accuracy of 99.3% with an AUC, and the proposed system surpassed the accuracy of 99.98% by 0.68%, indicating improvement when dealing with large datasets.

The Fourier transform achieved a 57% resolution,[4] indicating the superiority of Chebyshev waves. [7-9] However, the lack of integration of convolutional neural networks in these methods does not demonstrate their discrimination.

4. Conclusions

The novel hybrid system proposed in this work integrates convolutional neural networks with Chebyshev waveform transformation to create a DChWT-CNN hybrid system. This system utilizes deep learning to automatically detect fake faces, leveraging the orthogonality properties for data analysis and feature recognition in facial images, along with Chebyshev waves, to identify fake features with superior performance.

The exceptional performance demonstrated by the results on the FaceForensics++ dataset showed 99.98% accuracy, 99.91% classification accuracy, and 99.89% recall rate, along with a 2.3% improvement at F1 0.99, at 23 milliseconds per image. Confusion matrix analysis further confirms the system's efficiency.

It can be said that the proposed hybrid system holds great promise for the future in critical applications within the rapidly evolving technology landscape, such as cybersecurity and security fields like forensics and information security. This is because it has already successfully detected highly important fake faces. Future work will focus on detecting fake videos and real-time data, along with various other security applications to broaden the scope of this work.

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