IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Identification Of AI Generated Images Using Deep Learning

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ABSTRACT

Over the past few years, AI has revolutionized the creation of ultra-realistic face-swapped images, known as deepfakes. These images have become so convincing that they have often been nearly impossible to detect with the naked eye. While deepfake technology has been used for fun and entertainment, it has also had a dark side. It has spread political misinformation, been used for blackmail, and even created fake news about major events, causing serious harm. To tackle this growing problem, researchers have developed deep learning models to detect deepfakes. In this paper, we have introduced LBPNET, a new model designed to identify fake images more accurately. Our approach has started by analysing the fine details in an image's texture using Local Binary Pattern (LBP) features. These features have helped capture tiny differences that have set real and fake images apart. We have then used a Convolutional Neural Network (CNN) to train the system so it has been able to recognize deepfakes with greater precision.

I. INTRODUCTION

This document is a template. An electronic copy can be downloaded from the conference website. For questions on paper guidelines, please contact the conference publications committee as indicated on the conference website. Information about final paper submission is available from the conference website. With advancements in artificial intelligence (AI) and deep learning, deepfake technology has emerged as a powerful tool for generating highly realistic synthetic images and videos. These AI-generated manipulations can be used for entertainment, but they also pose serious risks such as misinformation, fraud, and identity theft. Detecting deepfakes has become a major challenge due to the sophistication of AI-based forgery techniques. This project introduces a deep learning-based deepfake detection system, called LBPNET, which integrates Local Binary Pattern (LBP) texture analysis with Convolutional Neural Networks (CNNs). The system effectively detects manipulated facial images and deepfake

videos by analysing texture inconsistencies and motion irregularities.

Deepfake images and videos can be indistinguishable to the human eye, making it difficult to verify authenticity. Current detection methods face the following challenges: Deepfake models are constantly improving, making traditional detection techniques ineffective. AI-generated images lack visible artifacts, making manual detection unreliable.

Existing detection methods require high computational resources and struggle with real-time deepfake detection.

To develop a hybrid deepfake detection model (LBPNET) that combines LBP feature extraction, CNN classification, analysis to accurately distinguish real and AI-generated images.

II. BASIC UNDERSTANDING

1. Deepfake Technology and Its Implications

Deepfake generation techniques use advanced AI models such as Generative Adversarial Networks (GANs) and Autoencoders to create realistic face-swapped images and videos. These deepfake models manipulate facial expressions, movements, and appearances in a way that makes detection challenging.

2. Deepfake Detection Methods

Existing deepfake detection techniques can be categorized into different approaches:

a. Feature-Based Detection

Analysing inconsistencies in facial features, such as unnatural blinking patterns, asymmetric facial expressions, and texture mismatches. Examining the lighting, shading, and edge inconsistencies in AI-generated images.

b. Deep Learning-Based Approaches

Convolutional Neural Networks (CNNs) are widely used for image classification and deepfake detection.

Convolutional Neural Network

A Convolutional Neural Network (CNN) is a type of deep learning algorithm designed for image recognition and classification. CNNs are widely used in deepfake detection because they can automatically learn and extract patterns, textures, and inconsistencies in AI-generated images.

CNN Architecture Used in the Project

1. Input Layer – Accepts images of size 224x224x1 (grayscale) or 224x224x3 (RGB).
2. Convolutional Layers – Extracts feature maps using filters (kernels).
3. Pooling Layers – Reduces spatial dimensions while preserving key features.
4. Fully Connected Layers – Processes extracted features for classification.
5. Softmax Layer – Outputs REAL or FAKE classification

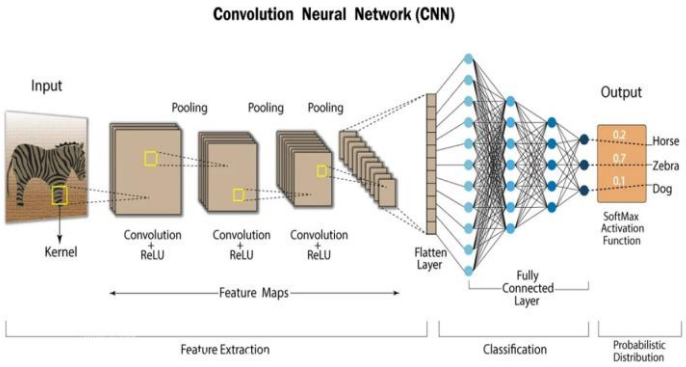

Fig.2.1 Convolutional Neural Network

Features and Functionalities

Advanced Deep Learning Algorithms

Uses Convolutional Neural Networks (CNNs)) model for feature extraction and classification.

Implements LBP-based Deep Learning (LBPNET) for texture analysis and pattern recognition.

Trains on a large dataset of real and fake images to improve detection accuracy.

Automated Detection of Fake Faces

The system automatically scans an uploaded image and analyses facial inconsistencies, artifacts and unnatural expressions.

It detects pixel-level alterations, such as blending artifacts and unnatural lighting, which are commonly found in deepfakes.

Real-Time Processing and High Accuracy

Capable of detecting fake content within seconds, reducing the time required for analysis.

Provides high detection accuracy compared to manual verification methods.

Secure and Scalable System

Uses cloud-based storage and processing to handle large volumes of images and videos.

Ensures data encryption and access control for security.

Can be scaled up to support multiple users simultaneously.

User-Friendly Interface

Provides an interactive dashboard for users to upload images and view detection results.
Displays detailed analysis reports, including probability scores for fake and real images.
Offers an easy-to-use interface that does not require technical expertise.

III. Working Mechanism

Step 1: Data Collection and Pre-processing

Fig-1 Real Image Datasets

Fig-2 AI Generayed Image Datasets

The system collects a large dataset of real and AI-generated fake images.
Pre-processing techniques such as data augmentation, face detection, and feature extraction are applied to improve model learning.

Step 2: Feature Extraction Using CNN & LBP

CNN extracts high-level features from images, such as facial patterns and structure.
LBP detects texture inconsistencies by analysing pixel variations and local patterns.

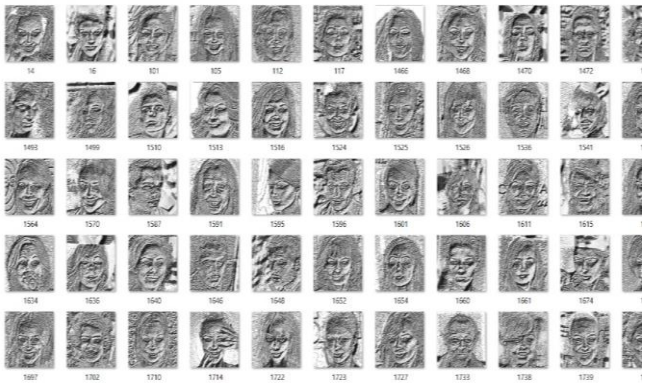

Fig-3 LBP FEATURE EXTRACTOR

1. Converted the image to grayscale → This helps in texture analysis without color interference.
2. Applied Local Binary Pattern (LBP) → It captures texture details by analyzing pixel intensity changes.
3. Generated a histogram of LBP features → This shows how different texture patterns are distributed.
4. Normalized the histogram → Ensures comparison consistency across images.
5. Plotted the LBP image and histogram → The left image shows LBP texture, and the right histogram shows frequency of LBP codes.

Real images have more diverse texture distributions with gradual variations.
AI-generated images often show irregular or uniform texture patterns because of artificial smoothness or unnatural sharpness.
Comparing this histogram with known real and fake images can help classify the image.

Understanding the Histogram of LBP Features
The histogram on the right side represents the distribution of LBP (Local Binary Pattern) codes found in the image. Here's how to interpret it:

1. X-axis (LBP Code):
Each bar corresponds to a unique LBP code, which represents a particular texture pattern.
These LBP codes range from 0 to 8 (because we used neighbours in LBP).
2. Y-axis (Normalized Frequency):
This represents how frequently each LBP pattern appears in the image.
The values are normalized (sum of all bars equals 1) so that different images can be compared fairly.

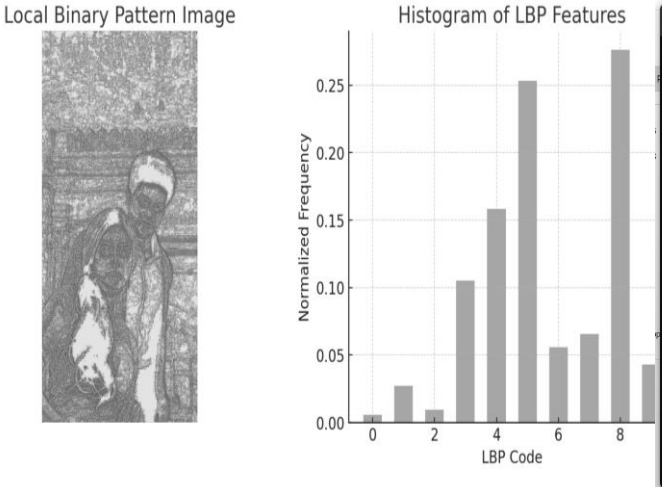

Fig-3 Histogram of LBP Features

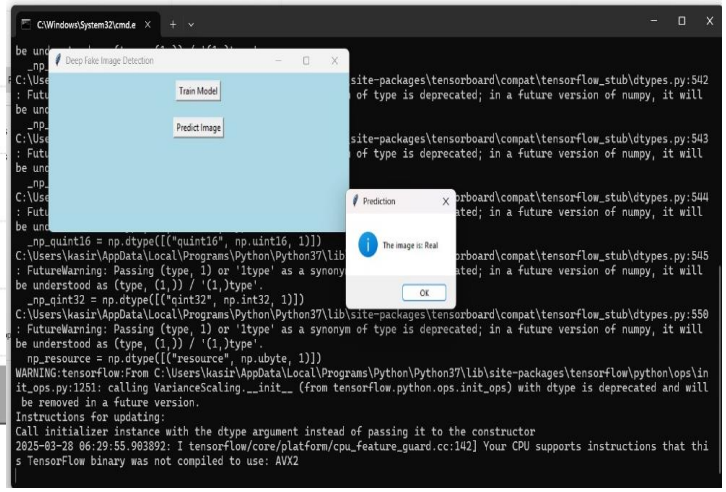

Fig-4 Output for Real Images

3. Observations from the Histogram:
Some LBP codes appear more frequently, meaning those textures dominate the image.
Others appear less often, indicating less common patterns.
A real image usually has a wider and smoother distribution, whereas AI-generated images tend to have sharper peaks and missing texture variations due to synthetic smoothness.

Step 3: Model Training and Classification
The model is trained using ResNet50 + LSTM to differentiate between real and fake images.
The training process includes binary classification (REAL vs. FAKE) with optimization techniques like Binary Cross-Entropy Loss to improve performance.

Step 4: Fake Image/Video Detection
When a new image or video is uploaded, the system applies the trained model to analyse the content.
It checks for inconsistencies in facial expressions, eye movements, lip-sync, and unnatural lighting.
The system assigns a confidence score indicating whether the image/video is real or fake.

Step 5: Result Generation and Reporting

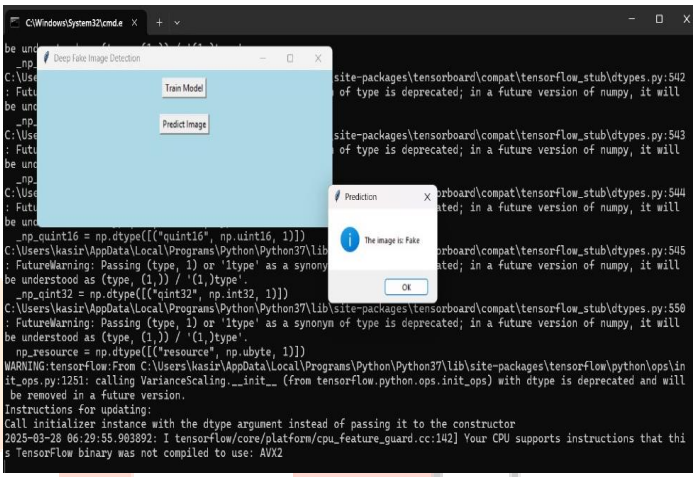

Fig-5 Output for AI Generated Images

The final result is displayed to the user with a probability score (e.g., 85% FAKE, 15% REAL).

IV. PERFORMANCE ANALYSIS

Analysis in Deepfake Detection System Performance analysis is crucial for evaluating the efficiency and accuracy of the Deepfake Detection System. Various metrics, techniques, and tools are used to assess the system's effectiveness in detecting manipulated media.

1. Performance Metrics

The following key metrics are used to analyse the system's performance:

A. Accuracy

Measures how many predictions (real vs. fake) are correct.

Formula: Accuracy = $\frac{(TP + TN)}{(TP + TN + FP + FN)}$

Example: If the system classifies 95 out of 100 images correctly, the accuracy is 95%.

B. Precision & Recall

Precision – Measures how many predicted deepfakes are actually deepfakes.

Recall (Sensitivity) – Measures how many actual deepfakes were correctly identified.

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

$$\text{Recall} = \frac{TP}{(TP + FN)}$$

Example: A high precision but low recall means the system is cautious but might miss some deepfakes.

C. F1-Score

Balances precision and recall to avoid bias.

$$\text{Formula: F1} = \frac{2 * \text{Precision} * \text{Recall}}{(\text{Precision} + \text{Recall})}$$

V. CONCLUSIONS

This project explored the identification of AI-generated images using traditional forensic techniques, deep learning models, and hybrid approaches. Traditional forensic methods (metadata analysis, edge detection, compression artifacts) are ineffective against advanced AI-generated images. Deep learning models (CNNs, RNNs) provide high accuracy but often struggle with generalization and computational efficiency. Hybrid approaches like LBPNET (LBP + CNN) offer a balance between accuracy, speed, and generalization, making them suitable for real-time deepfake detection. Challenges such as adversarial attacks, computational cost, and real-time feasibility remain key concerns in the field.

1.Contributions of This Project

Developed a hybrid model (LBPNET) that enhances deepfake detection through texture analysis and deep learning.

Conducted a performance analysis, proving that LBPNET is faster and more robust compared to traditional CNN-based models.

Provided insights into the limitations of existing methods and proposed solutions for real-time implementation

Addressed generalization issues by testing models on multiple deepfake datasets.

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