MORPH DETECTION

A DESIGN PROJECT REPORT

submitted by

SANJAY RAMAJAYAM M

SUDEESH B

SUNDAR B

in partial fulfilment for the award of the degree of

BACHELOR OF ENGINEERING

in

COMPUTER SCIENCE AND ENGINEERING

K RAMAKRISHNAN COLLEGE OF TECHNOLOGY

(An Autonomous Institution, affiliated to Anna University Chennai, Approved by AICTE, New Delhi)

SAMAYAPURAM – 621 112

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BONAFIDE CERTIFICATE

Certified that this project report titled **"MORPH DETECTION"** is the bonafide work of **SANJAY RAMAJAYAM M (811722104131), SUDEESH B(811722104160), SUNDAR B (811722104161)** who carried out the project under my supervision. Certified further, that to the best of my knowledge the work reported here in does not form part of any other project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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DECLARATION

We jointly declare that the project report on **"MORPH DETECTION"** is the result of original work done by us and best of our knowledge, similar work has not been submitted to **"ANNA UNIVERSITY CHENNAI"** for the requirement of Degree of **Bachelor OF Engineering**. This project report is submitted on the partial fulfilment of the requirement of the awardof Degree of **Bachelor OF Engineering.**

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ACKNOWLEDGEMENT

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ABSTRACT

The increasing sophistication of digital image editing tools has led to a growing threat in the field of biometric security: morphing attacks. Morph detection systems are crucial in identifying and mitigating these threats by detecting digitally altered images that seamlessly blend facial features from two or more individuals. These morphed images can deceive conventional biometric systems, posing significant risks in applications such as passport issuance, automated border control, and secure access systems. The primary objective of morph detection is to ensure the integrity of identity verification processes by employing advanced algorithms and machine learning techniques to analyze and authenticate biometric data. By enhancing detection accuracy and robustness, morph detection systems play a pivotal role in safeguarding against identity fraud and maintaining trust in digital security infrastructures.

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LIST OF ABBREVIATIONS

ABBREVIATION	FULL FORM
AI	Artificial Intelligence
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
ROI	Region of Interest
MFA	Multi-Factor Authentication
GDPR	General Data Protection Regulation
LBP	Local Binary Patterns
GANs	Generative Adversarial Networks
PRNU	Photo-Response Non-Uniformity
SSL/TLS	Secure Sockets Layer/Transport Layer Security
AWS	Amazon Web Services
TPU	Tensor Processing Unit

CHAPTER 1
INTRODUCTION

1.1 BACKGROUND

The advent of advanced imaging and editing technologies has given rise to new challenges in the field of biometric security, particularly with the increasing prevalence of morphing attacks. A morph detection system is designed to counteract these threats by identifying digitally altered images that combine features from two or more individuals, making it difficult for conventional security systems to detect anomalies. These morphed images pose significant risks, especially in contexts such as passport issuance and automated border control, where accurate identity verification is crucial. The primary goal of a morph detection system is to safeguard against identity fraud by employing sophisticated algorithms and machine learning techniques to scrutinize and authenticate biometric data. By enhancing the accuracy and robustness of biometric systems, morph detection technologies play a vital role in maintaining the integrity of identity verification processes, ensuring both security and trust in digital interactions.

Fig 1.1 Flow Control

1.2 OVERVIEW

The Morph Detection System is an advanced platform designed to combat the growing threat of manipulated facial images used in identity fraud and document forgery. By leveraging cutting-edge AI techniques, this system provides a reliable and efficient solution for identifying morphed images, ensuring the integrity of biometric verification processes. Its primary objective is to bridge the gap between the increasing sophistication of morphing techniques and the need for secure identity verification systems across industries.This system enables organizations to analyze and detect subtle inconsistencies in facial images, such as asymmetries in facial landmarks, texture anomalies, and lighting discrepancies. Users can upload images for verification, and the system processes them to flag potential morphing attempts. It ensures high accuracy by combining advanced feature extraction techniques and machine learning algorithms, empowering users to make well-informed decisions during identity verification.Real-time image analysis and a user-friendly interface enhance the

accessibility of the platform for both security professionals and non-technical users. Additionally, the system supports integration with existing biometric verification processes, streamlining operations and increasing security. On the backend, AI models analyze facial characteristics and compare them to pre-stored authentic data, ensuring consistent performance even against highly sophisticated morphing attempts.The Morph Detection System thus plays a crucial role in industries such as law enforcement, border control, and financial institutions, safeguarding against fraudulent activities and ensuring trust in identity verification systems.

1.3 PROBLEM STATEMENT

As facial morphing techniques grow increasingly sophisticated, traditional methods of identity verification and biometric authentication face significant challenges in detecting manipulated images. The lack of an automated, accurate detection system has led to vulnerabilities in processes such as passport issuance, visa approvals, and financial account creation. These gaps expose organizations and individuals to risks like identity theft and fraud.The primary problem lies in the inability of conventional systems to detect subtle yet impactful changes in facial images, such as blended facial features or seamlessly merged identities. Manual methods for verifying images are time-consuming, prone to human error, and increasingly ineffective as morphing techniques evolve. Furthermore, organizations often lack a centralized solution to analyze, track, and log detected anomalies, making it difficult to respond to fraudulent activities proactively.This project aims to address these issues by introducing an automated morph detection system capable of accurately identifying manipulated facial images. By providing a robust, real-time solution, the system ensures that organizations can safeguard their operations against identity fraud and maintain the integrity of their verification processes.

1.4 OBJECTIVE

The primary objective of the Morph Detection System is to develop an advanced, user-friendly platform that automates the detection of facial morphing in identity verification processes. This system aims to enhance the accuracy and reliability of biometric authentication by leveraging AI-powered tools to analyze facial landmarks, textures, and lighting patterns for inconsistencies that indicate manipulation. By integrating seamlessly with existing verification workflows, the system supports real-time detection and ensures scalability for industries such as border control, financial services, and law enforcement.

Additionally, the platform provides centralized administrative tools for tracking and logging detection results, generating detailed reports, and ensuring robust security against fraudulent activities. Ultimately, the Morph Detection System seeks to strengthen identity verification processes, mitigate risks of identity fraud, and maintain trust in digital authentication systems.

1.5 IMPLICATION

The implementation of the Morph Detection System carries significant implications across various domains, ensuring enhanced security and trust in identity verification processes. In the realm of biometric authentication, the system fortifies the integrity of applications such as passport issuance, visa processing, and financial account creation by detecting morphing attempts with high accuracy. This reduces the risks associated with identity theft and fraud, safeguarding individuals and organizations from potentially severe financial and reputational damages.For law enforcement and border control, the system provides a reliable tool to prevent unauthorized access or misuse of government-issued IDs, enabling quicker, more efficient screenings and reducing operational delays. In industries like banking and healthcare, where secure identity verification is critical, the system fosters trust and compliance with regulations by ensuring authenticity in customer identification processes.Furthermore, the system sets a benchmark for technological innovation in the fight against digital manipulation. By offering a scalable, AI-driven solution, it helps organizations stay ahead of evolving threats, ensuring preparedness against increasingly sophisticated morphing techniques. The integration of such a robust detection system not only enhances operational efficiency but also reinforces public trust in digital authentication and verification systems, paving the way for more secure and transparent digital ecosystems.

CHAPTER 2
LITERATURE SURVEY

1. TITLE : DEEPFAKE DETECTION WITH CNN
AUTHORS : Yuezum Li and Siwei Lyu
YEAR : 2018

This paper presents a method for detecting deepfakes by identifying visual artifacts using Convolutional Neural Networks (CNNs). The model was trained on a dataset of deepfake videos and achieved high accuracy in detecting tampered content by focusing on inconsistencies in facial features. This approach utilizes CNNs to analyze facial inconsistencies that are commonly present in synthetic media, making it effective for detecting deepfake videos.

2. TITLE : EXPOSING DEEPFAKE VIDEOS BY DETECTING FACE WRAPPING ARTIFACTS
AUTHORS : Hany Farid and Shruthi Agarwal
YEAR : 2019

This study introduces a deepfake detection approach that focuses on detecting face warping artifacts, a common indicator of manipulation in deepfake videos. By analyzing inconsistencies in facial proportions, the system effectively identifies manipulated content. The research highlights that these warping artifacts provide a reliable cue for recognizing synthetic media, especially in cases where face swapping or other facial manipulations have occurred.

3. TITLE : A SURVEY ON DEEPFAKE DETECTION METHODS: CHALLENGES AND FUTURE DIRECTIONS
AUTHORS : Shu Hu, Siqi Zheng, and Rajesh Gupta

YEAR : 2020

This paper provides a comprehensive survey of deepfake detection methods, exploring current techniques, challenges, and potential improvements. It examines both manual and automated approaches, discussing the adaptability of detection methods in response to evolving deepfake technologies. The study emphasizes the need for new detection techniques that can keep up with the rapid development of deepfake creation methods.

4. TITLE : PROTECTING WORLD LEADERS AGAINST DEEPFAKES
AUTHOR : Michaël L. L. G. Van Der Torre & Hany Farid
YEAR : 2020

This study explores a real-time monitoring system designed to detect and prevent deepfake videos targeting high-profile individuals, such as world leaders. The paper outlines a framework that uses automated systems to detect altered videos and offers protection mechanisms against the misuse of deepfake technologies. The research focuses on leveraging both AI and human oversight to provide robust countermeasures against deepfake threats in political and security contexts.

5. TITLE : DEEPFAKE DETECTION USING RNN ON TEMPORAL PATTERNS
AUTHORS : Tolosana, R., Vera-Rodriguez, R., Fierrez, J., & Ortega.
YEAR : 2021

This study presents a recurrent neural network (RNN)-based deepfake detection model that identifies synthetic media by analyzing temporal patterns such as blinking rates and facial muscle movements. By focusing on inconsistencies between frames, the model offers a promising approach for real-time detection of deepfakes in video content. The

research demonstrates how temporal analysis can effectively identify subtle manipulation cues that are not always apparent in individual frames.

CHAPTER 3

SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

Existing morph detection systems largely rely on traditional methods for identifying manipulated images, with a focus on manual analysis and basic feature extraction techniques. While these systems are functional in some contexts, they face several limitations:

TRADITIONAL IMAGE ANALYSIS METHODS

- Manual Inspection: Current systems often depend on human experts to visually inspect images for inconsistencies. This process is time-consuming, prone to human error, and often ineffective against high-quality morphs.
- Limited Detection Capabilities: These methods typically analyze basic facial features like eye position and skin tone, but they fail to detect more complex morphing techniques such as blending and pixel-level manipulation.
- No Automation: Traditional systems do not automate the identification of morphed images, leading to delays and inefficiencies in biometric systems that require rapid verification, such as passport control or identity authentication.

MACHINE LEARNING-BASED SYSTEMS

1.Basic Deep Learning Models

Many current morph detection systems use basic deep learning models that focus on facial feature recognition but lack the sophistication needed to detect subtle artifacts or sophisticated morphing techniques.These models often operate on static facial data and are not equipped to handle dynamic, real-time applications, limiting their use in biometric verification systems that need real-time results.

2.Limited Dataset and Model Training

Existing systems are often trained on smaller, less diverse datasets, limiting their ability to generalize across different manipulation techniques or facial variations.A lack of

advanced data augmentation and transfer learning capabilities prevents these systems from adapting quickly to emerging morphing techniques.

3.Manual and Static Feedback

Many systems rely on static feedback and are unable to learn from new types of manipulated data, reducing the ability to continuously improve detection performance in the face of evolving threats.

The existing morph detection systems primarily rely on traditional image analysis methods, which often involve manual inspection or basic feature extraction techniques. These systems analyze facial features such as the positioning of eyes, mouth, and skin tone to detect potential manipulations. However, they fall short when it comes to detecting more sophisticated morphing techniques, such as subtle blending of features or pixel-level distortions. Most existing systems are limited to static, low-quality datasets, which hampers their ability to identify advanced morphing methods that may not fit the characteristics of the training data. Additionally, these systems are often slow, as they do not offer real-time detection capabilities, making them unsuitable for environments requiring fast decision-making, such as border control or biometric verification. Furthermore, the lack of automation in many systems leads to delays, as human experts are required for verification, increasing the risk of errors and inefficiencies. While some systems have begun using deep learning for feature extraction, they are still basic in their approach, unable to adapt dynamically to new types of morphing techniques or to handle large, varied datasets. This highlights the need for more advanced, scalable, and automated solutions to address the evolving challenges of morph detection.

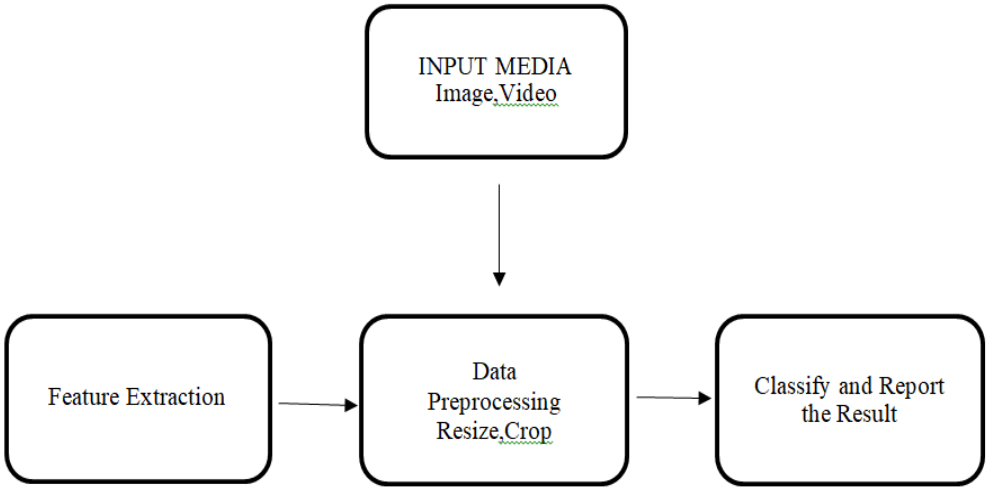

FIG 3.1. SYSTEM ARCHITECTURE

3.2 PROPOSED SYSTEM

The proposed Morph Detection System is a highly advanced, AI-driven platform designed to address the growing challenges of detecting morphed images and videos, which are often used in identity theft and fraudulent activities. Unlike traditional systems that rely on basic feature extraction or manual inspection, this system leverages cutting-edge deep learning models, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), to analyze both spatial and temporal aspects of images and videos in real time. The system is trained to identify a wide range of facial manipulations, from subtle blending of facial features to more complex techniques like deepfake generation. One of the key innovations of this system is its ability to continuously improve and adapt by utilizing transfer learning and data augmentation techniques, enabling the system to stay ahead of evolving morphing methods. **Fig 3.1 System architecture** ets that cover different types of image manipulations and various facial variations, the system can generalize effectively and maintain high accuracy even with new types of morphing techniques that may not have been previously encountered. This is especially critical as morphing techniques become more sophisticated, making it harder for traditional detection methods to keep up. The system offers real-time processing capabilities, ensuring that morphed images or videos can be flagged immediately as part of biometric verification, border control systems, or secure document verification processes. It is designed to handle both still images and video data, enabling it to detect inconsistencies across multiple frames, such as unnatural facial

movements or blinking rates, which are often indicative of manipulation. Additionally, the user interface of the system is designed to be intuitive and responsive, offering seamless access to detection results, even on mobile devices. The platform includes a centralized dashboard for administrators to monitor flagged content, review performance analytics, and track system status in real time. Moreover, the system ensures data security and integrity by using encryption protocols for both image data and user transactions, making it suitable for use in sensitive environments where privacy is paramount. For ease of integration, the system supports cloud-based architecture, allowing for scalable deployment across organizations of varying sizes and sectors. Whether used in financial institutions, government agencies, or healthcare providers, the system can adapt to diverse environments and growing user bases.

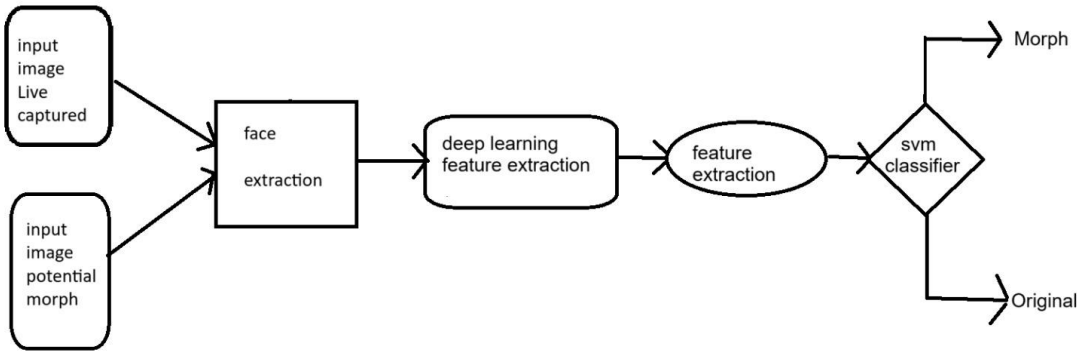

Fig 3.2 Proposed system architecture

3.3 BLOCK DIAGRAM

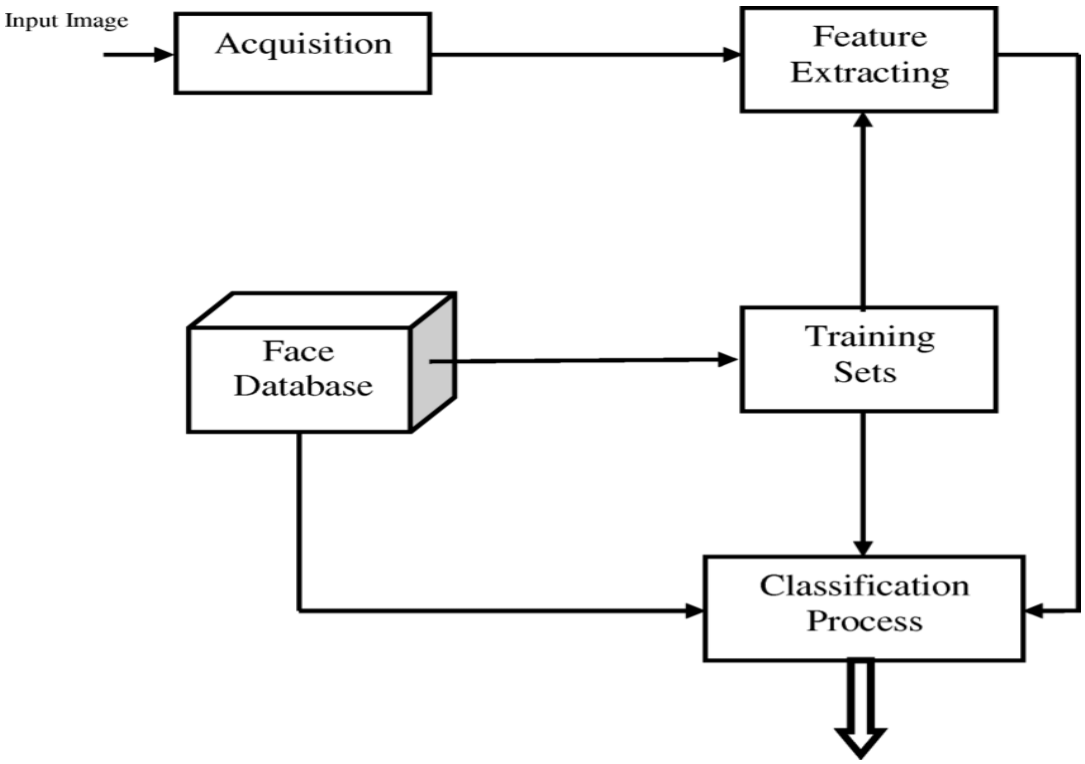

Fig 3.3 block diagram

3.3.1 USE CASE DIAGRAM

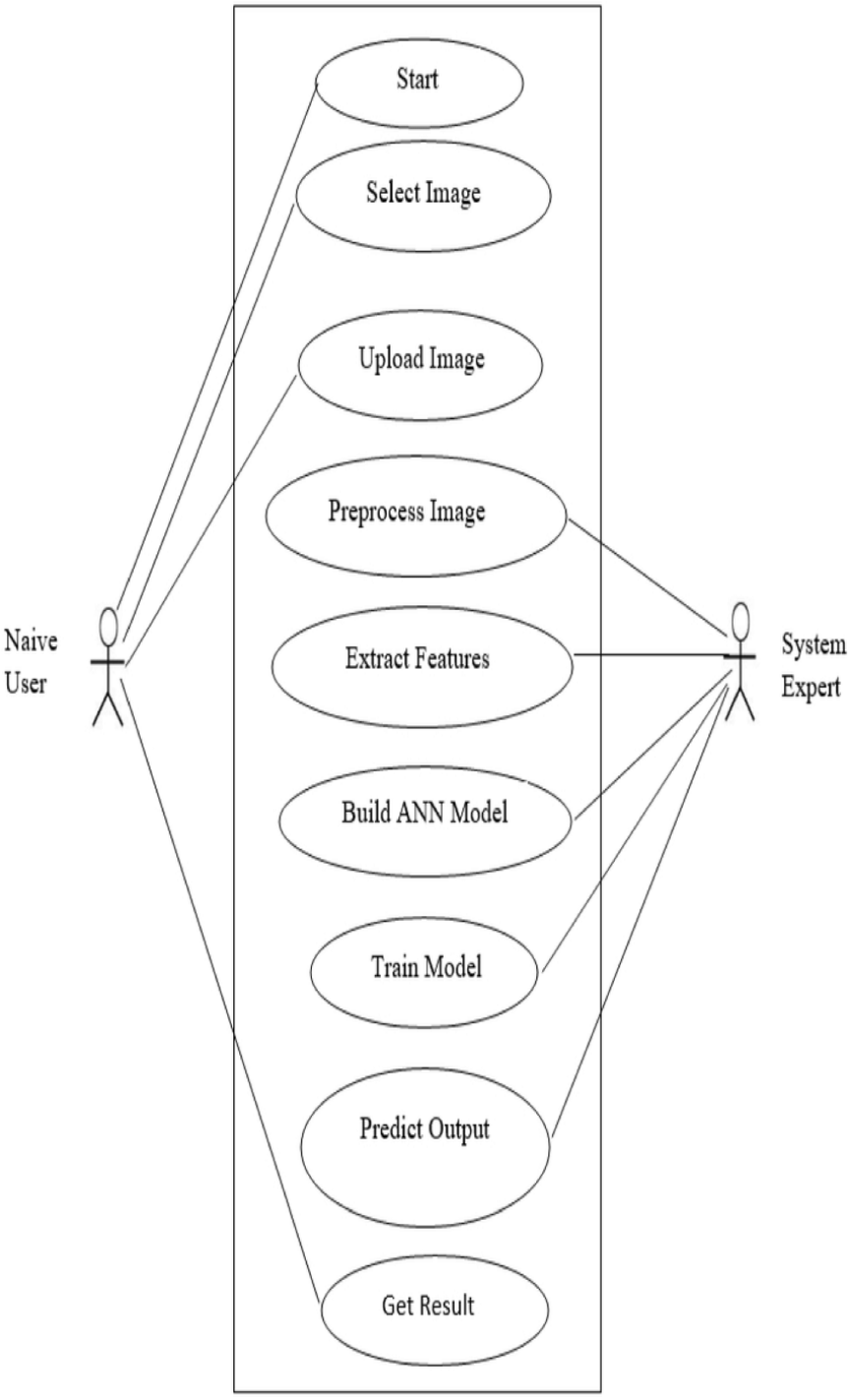

Fig 3.4 Use case Diagram

3.4 FLOWCHART

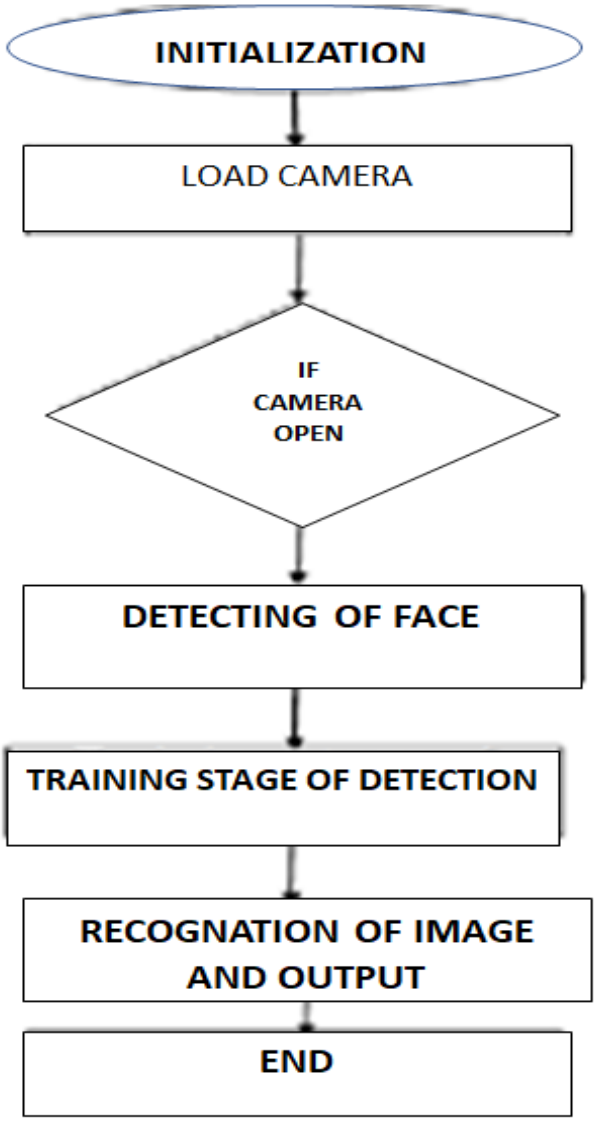

Fig 3.5 Flow chart

3.5 PROCESS CYCLE

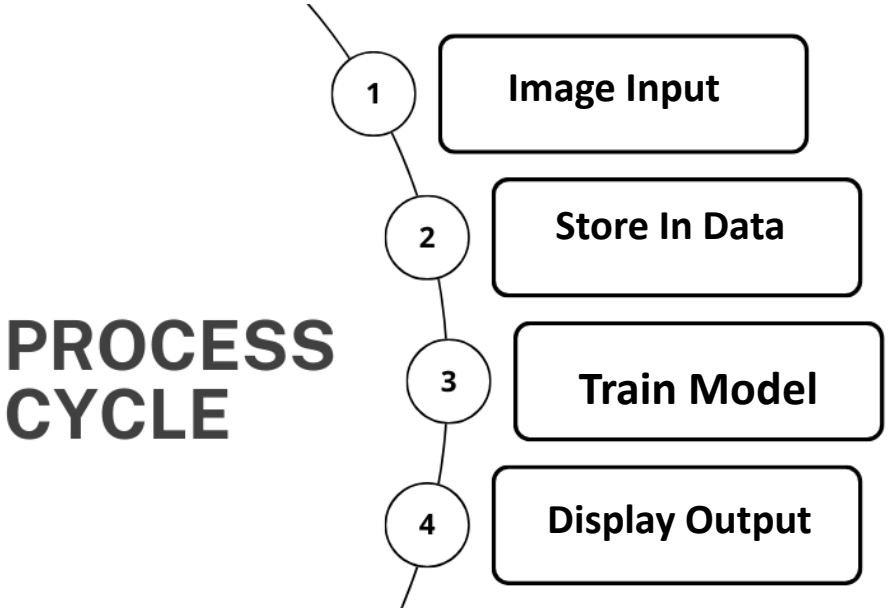

Fig 3.6 Life Cycle of the Process

3.6 ACTIVITY DIAGRAM

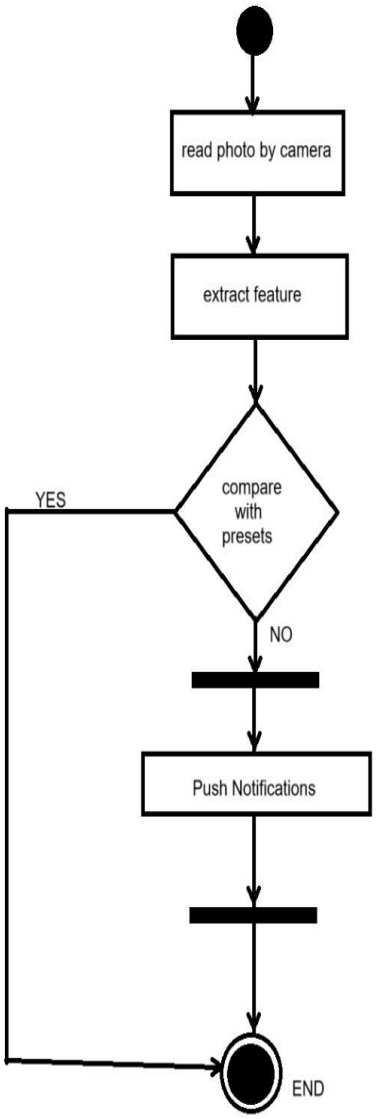

Fig 3.7 Activity diagram

CHAPTER 4

MODULES

4.1 MODULE DESCRIPTION

- Data Acquisition Module
- Preprocessing Module
- Feature Extraction Module
- Morph Detection Module
- Authentication and Reporting Module

4.1.1 Data Acquisition Module

Objective: To collect media data, either from live video feeds, pre-recorded files, or images, serving as the entry point for content that will undergo deepfake analysis.

Features:

- **Input Sources:** Media can be acquired from various sources such as video cameras, storage systems, or direct media uploads.
- **Media Format Processor:** Converts input media into standard formats suitable for processing.
- **Data Transfer:** The module ensures the collected data is transferred to the preprocessing module for further analysis.
- **Technologies:** Python, OpenCV, Media Processing Tools

4.1.2 Preprocessing Module

Objective: To prepare the collected data for deepfake analysis by standardizing and enhancing it, ensuring it is optimized for feature extraction and improving detection accuracy.

Features:

- **Image/Video Resizer:** Adjusts the resolution of media to the required dimensions.

- **Noise Reduction Filters:** Applies noise reduction filters to clean the media for better feature extraction.
- **Face Detection Algorithm:** Detects and isolates faces in each frame, ensuring the relevant areas are focused on for further analysis.
- **Technologies:** Python, OpenCV, TensorFlow, Dlib, Face Detection Algorithms

4.1.3 Feature Extraction Module

Objective: To analyze media frames and extract unique features that may indicate manipulation, identifying the subtle differences between real and altered media.

Features:

- **Facial Landmark Detector:** Identifies key facial landmarks (eyes, nose, mouth) for symmetry and consistency analysis.
- **Texture Analysis:** Analyzes skin texture, lighting inconsistencies, and pixel patterns.
- **Motion Analysis (for video):** Assesses the consistency of natural motion across frames to detect irregularities.
- **Technologies:** Python, TensorFlow, OpenCV, Keras, Computer Vision Techniques

4.1.4 Morph Detection Module

Objective: To detect and identify facial morphing manipulations in images and videos by analyzing inconsistencies in facial features and movements across frames.

Features:

- **Facial Feature Matching:** Compares key facial features like eyes, nose, and mouth for unnatural alignments or distortions that are typical in morphed faces.
- **Pixel-Level Analysis:** Identifies anomalies in pixel patterns that suggest manipulation, such as unnatural blending or pixel distortions at the boundaries of faces.
- **Consistency Checking:** Verifies the consistency of facial features across multiple frames or images to detect temporal or spatial morphing artifacts.
- **Deepfake Technique Identification:** Classifies the type of morphing manipulation, such as face swapping, facial expression manipulation, or other adversarial alterations.
- **Technologies:** Python, OpenCV, Dlib, TensorFlow, CNNs

4.1.5 Authentication and Reporting Module

Objective: To verify the authenticity of detected faces and generate detailed reports about the morphing process, providing insights into the detected manipulations.

Features:

- **Authentication Verification:** Cross-checks detected faces against a database of known authentic individuals to ensure accuracy in identification.
- **Detailed Report Generation:** Generates reports highlighting the detected manipulations, including the type of morphing, confidence scores, and affected facial regions.
- **Visualization Tools:** Provides visual feedback by overlaying detected manipulations on the image or video to highlight specific alterations.
- **Database Integration:** Saves detection results and historical data for further analysis or audits.
- **Technologies:** Python, MySQL, HTML/CSS, JavaScript, Reporting Tools

CHAPTER 5

SYSTEM SPECIFICATION

5.1 HARDWARE SPECIFICATION

- Camera: High-definition webcam or video capture device for image and video input.
- RAM: 8GB or more for efficient processing and memory handling during model training and real-time detection.
- Power Supply: DC Power for continuous operation, ensuring stable system performance during long-duration processing.

5.2 SOFTWARE SPECIFICATION

- Operating System: Windows OS (Windows 10 or higher) for compatibility with software tools and frameworks.
- Programming Language: Python (for model development, data processing, and feature extraction)

CHAPTER 6

METHODOLOGY

6.1 PERFORMANCE OPTIMIZATION

1. Preprocessing Optimization

- **Resize Images:** Resize images to a consistent and smaller resolution to reduce computational load.
- **Normalize Input:** Use normalization techniques (e.g., mean subtraction, division by standard deviation) to improve model stability.
- **Focus on ROI:** Use region-of-interest (ROI) extraction to focus processing on specific parts of the image.

2. Algorithmic Improvements

- **Feature Extraction:**
  - Use lightweight feature extractors (e.g., MobileNet, EfficientNet) for faster inference.
  - Extract high-quality features using edge detectors or texture-based descriptors.
- **Dimensionality Reduction:** Use PCA, t-SNE, or UMAP to reduce feature set size without losing critical information.

3. Model Optimization

- **Model Quantization:** Convert weights to lower precision (e.g., float32 to int8) to improve runtime on hardware like CPUs and GPUs.
- **Pruning:** Remove redundant layers or neurons in neural networks without sacrificing significant accuracy.
- **Efficient Architectures:** Use compact architectures like YOLO, MobileNet, or lightweight CNNs optimized for speed.

4. Parallelism and Acceleration

- **GPU/TPU Utilization:** Leverage GPUs or TPUs for parallel processing.
- **Batch Processing:** Process multiple images simultaneously in batches to maximize resource utilization.
- **Multithreading/Multiprocessing:** Implement threading or multiprocessing to divide the workload across multiple cores.

5. Dataset and Training Optimization

- **Balanced Dataset:** Ensure a balanced dataset to avoid bias and improve model robustness.
- **Data Augmentation:** Use augmentations like rotation, flipping, and scaling to increase diversity.
- **Transfer Learning:** Fine-tune pre-trained models to save time and computational resources.

6. Software-Level Optimization

- **Framework Tuning:** Use optimized libraries (e.g., TensorFlow Lite, ONNX Runtime, OpenVINO) for inference.
- **Custom Kernels:** Write low-level kernels for specific tasks (e.g., CUDA for Nvidia GPUs).
- **Lazy Evaluation:** Evaluate computational steps only when necessary.

7. Hardware Optimization

- **Edge Devices:** Deploy models on devices with optimized hardware for inference, such as NVIDIA Jetson or Google Coral.
- **FPGA/ASIC:** Use custom hardware solutions tailored to morph detection.

8. Application-Specific Strategies

- **Ensemble Models:** Combine multiple models to improve detection accuracy while balancing speed.

6.2 DEVELOPMENT APPROACH

1. **Define Objectives and Requirements**

- Identify use cases (e.g., security, forensics) and performance metrics like accuracy and speed.

2. **Data Collection and Preparation**

- Gather authentic and morphed images, label them, apply augmentations, and preprocess for consistency.

3. **Feature Extraction**

- Use traditional methods (e.g., LBP, Fourier Transform) or deep learning (e.g., CNNs) to identify morph features.

4. **Model Development**

- Train models using traditional machine learning (e.g., SVM) or deep learning (e.g., ResNet). Use transfer learning for efficiency.

5. **Evaluation and Optimization**

- Validate models using metrics like precision and F1-score. Optimize models with quantization, pruning, and caching.

6. **System Integration**

- Automate preprocessing, support real-time and batch pipelines, and integrate with APIs or user interfaces.

7. **Testing and Deployment**

- Perform functional, stress, and edge case testing. Deploy via cloud, on-premises, or edge devices with containerization.

8. **Continuous Improvement**

- Update models with new data, optimize pipelines, and use monitoring tools for system performance.

6.3 WORKFLOW

1. Input and Preprocessing

- **Image Upload:** User uploads an image or video for analysis.
- **Preprocessing:**
    - Resize and compress the image to a standard resolution.
    - Normalize pixel values for consistency.
    - Optionally apply noise reduction or sharpening for enhanced analysis.

2. Feature Extraction

- Extract distinguishing features using:
    - **Traditional Methods:** Edge detection, texture analysis (e.g., LBP).
    - **Deep Learning:** Feature maps from CNNs or transformers.

3. Morph Detection Analysis

- **Model Inference:**
    - Pass features or preprocessed images through a trained model.
    - Use lightweight or pre-trained models for real-time detection.
- **Output Classification:**
    - Determine if the input is "Morphed" or "Authentic."
    - Optionally provide confidence scores or highlight morphed regions.

4. Caching and Optimization

- **Caching:**
    - Store results using unique image hashes to prevent reprocessing.
- **Batch or Lazy Processing:**
    - Process multiple images in batches or on-demand for efficiency.

5. Result Storage and Logging

- Log detection results, timestamps, and metadata in a database.
- Index frequently queried fields (e.g., image hash, detection result) for fast retrieval.

6. Output and Feedback

- **Display Results:**
  - Provide detection results via user interface or API.
  - Include confidence scores and visual annotations if applicable.
- **User Feedback:**
  - Allow users to report false positives or negatives for model improvement.

7. Monitoring and Updates

- Use monitoring tools to track performance metrics and system health.
- Periodically update the detection model with new data to improve accuracy.

6.4 TECHNOLOGIES USED

1. **Image Processing**

- Tools: OpenCV, scikit-image, Pillow.
- Techniques: Local Binary Patterns (LBP), Fourier Transform, Gabor Filters.

2.**Machine Learning and Deep Learning**

- ML Algorithms: SVM, Random Forest, Gradient Boosting.
- DL Models: CNNs, Transfer Learning (e.g., ResNet, MobileNet), Vision Transformers.
- Frameworks: TensorFlow, PyTorch, Scikit-learn.

3. **Optimization and Caching**

- Tools: Redis, Memcached for caching; TensorRT for model optimization.

4.**Database**

5.**Deployment and Scaling**

- Tools: Docker, Kubernetes, NGINX, HAProxy.
- Cloud: AWS, Google Cloud, Azure.

- **Monitoring and Analytics**

- Tools: Prometheus, Grafana, ELK Stack for logging and system health

6.5 TOOLS AND RESOURCES

- Image Processing: OpenCV, Pillow, scikit-image.
- ML/DL Frameworks: TensorFlow/Keras, PyTorch.
- Pre-trained Models: ResNet, MobileNet, Vision Transformers.
- Databases: MySQL, PostgreSQL (SQL), MongoDB (NoSQL).
- Optimization: TensorRT, ONNX Runtime, Redis, Memcached.
- Deployment: Docker, Kubernetes, NGINX, HAProxy.
- Datasets: FaceForensics++, CASIA-WebFace, OpenMorphed.
- Monitoring: Prometheus, Grafana, ELK Stack.

6.6 SECURITY MEASURES

`1.**Data Encryption**

- Encrypt images and sensitive data during transmission (SSL/TLS) and at rest (AES) to protect against unauthorized access.

2. **Access Control**

- Implement role-based access control (RBAC) to restrict who can view or process images.
- Use multi-factor authentication (MFA) for system access.

3. **Input Validation**

- Validate incoming images to ensure they are from trusted sources, preventing malicious input like malware or corrupted files.

4.**Model Security**

- Protect detection models from reverse engineering by obfuscating model code or using secure deployment platforms (e.g., AWS SageMaker, Google AI Platform).
- Monitor and mitigate adversarial attacks that try to deceive the model.

5.**Audit Trails**

- Log all detection requests, results, and user actions for auditing and tracking suspicious activities.

6. **Data Anonymization**

- Anonymize or mask sensitive data, such as facial features, in processed images to comply with privacy regulations (e.g., GDPR).

7. **Regular Security Audits**

- Conduct regular security assessments to identify vulnerabilities in the system, including penetration testing and code reviews.

8.**Secure Cloud and Edge Deployments**

- Use cloud services with built-in security features (e.g., IAM, VPC) and secure edge devices with proper firmware updates and protection mechanisms.

CHAPTER 7

CONCLUSION AND FUTURE ENHANCEMENT

7.1 CONCLUSION

Morph detection plays a crucial role in maintaining the integrity of digital media, ensuring security, and preventing image manipulation in applications like forensics, media verification, and authentication. By leveraging advanced image processing techniques, machine learning, and deep learning models, morph detection systems can accurately identify tampered content.To build an effective and scalable morph detection system, it is essential to use a combination of powerful tools, secure data handling practices, and optimized processing pipelines. Additionally, continuous improvement through model updates and monitoring ensures that the system stays robust against evolving manipulation techniques.With the growing importance of digital content security, investing in reliable morph detection solutions is critical for organizations aiming to protect their data and uphold trust in digital media.

7.2 FUTURE ENHANCEMENT

Future enhancements for morph detection systems include integrating deep learning frameworks like MTCNN and FaceNet for improved accuracy, leveraging multimodal biometric systems that combine face, fingerprint, and iris recognition to increase robustness against spoofing, and utilizing 3D biometric imagery for precise feature representation. Additionally, incorporating spatial attention mechanisms can enhance feature detection, while PRNU (Photo-Response Non-Uniformity) variance analysis provides a robust method for identifying morphed images by examining variations within the image caused by morphing. These advancements aim to create more secure and reliable morph detection systems.

APPENDIX -1

SOURCE CODE

PREDICT.PY

```
import tensorflow as tf
import numpy as np

from tkinter import *
import os
from tkinter import filedialog
import dlib
import cv2
import time
from matplotlib import pyplot as plt
from tkinter import messagebox
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing.image import img_to_array, load_img

def endprogram():
    print("\nProgram terminated!")
    sys.exit()


def fulltraining():
    import Model as mm


def testing():
    global testing_screen
    testing_screen = Toplevel(main_screen)
    testing_screen.title("Testing")
    # login_screen.geometry("400x300")
    testing_screen.geometry("600x450+650+150")
    testing_screen.minsize(120, 1)
    testing_screen.maxsize(1604, 881)
```

```
    testing_screen.resizable(1, 1)
    testing_screen.configure(bg='cyan')
    # login_screen.title("New Toplevel")

    Label(testing_screen, text="'Upload Video'", disabledforeground="#a3a3a3",
          foreground="#000000", width="300", height="2", bg='cyan', font=("Calibri",
16)).pack()
    Label(testing_screen, text="").pack()
    Label(testing_screen, text="").pack()
    Label(testing_screen, text="").pack()
    Button(testing_screen, text="'Upload Video'", font=(
        'Verdana', 15), height="2", width="30", bg='cyan', command=imgtest).pack()


global affect


def imgtest():
    import_file_path = filedialog.askopenfilename()

    model = load_model('Model/deepfake-detection-model.h5')

    input_shape = (128, 128, 3)
    pr_data = []
    detector = dlib.get_frontal_face_detector()
    cap = cv2.VideoCapture(import_file_path)
    frameRate = cap.get(5)
    while cap.isOpened():
        frameId = cap.get(1)
        ret, frame = cap.read()
        if ret != True:
            break
        if frameId % ((int(frameRate) + 1) * 1) == 0:
            face_rects, scores, idx = detector.run(frame, 0)
```

```
        for i, d in enumerate(face_rects):
            x1 = d.left()
            y1 = d.top()
            x2 = d.right()
            y2 = d.bottom()
            crop_img = frame[y1:y2, x1:x2]
            data = img_to_array(cv2.resize(crop_img, (128, 128))).flatten() / 255.0
            data = data.reshape(-1, 128, 128, 3)
            # print(model.predict_classes(data))
            result = model.predict(data)
            ind = np.argmax(result)
            out=''

            if ind == 0:
                out = "Fake"
            elif ind == 1:
                out = "Real"
            print(out)
            cv2.putText(crop_img, out, (10, 25), cv2.FONT_HERSHEY_SIMPLEX, 0.7, (0,
255, 0), 2)
            # cv2.imshow("cropped", cropped)
            cv2.imshow("Output", crop_img)
            cv2.waitKey(0)


def image():
    import_file_path = filedialog.askopenfilename()

    model = load_model('Model/deepfake-detection-model.h5')


    #cap = cv2.VideoCapture(import_file_path)
    #frameRate = cap.get(5)
    crop_img = cv2.imread(import_file_path)
```

```
    data = img_to_array(cv2.resize(crop_img, (128, 128))).flatten() / 255.0
    data = data.reshape(-1, 128, 128, 3)
    # print(model.predict_classes(data))
    result = model.predict(data)
    ind = np.argmax(result)
    out = ''

    if ind == 0:

        out = "Fake"

    elif ind == 1:

        out = "Real"

    print(out)

    cv2.putText(crop_img, out, (10, 25), cv2.FONT_HERSHEY_SIMPLEX, 0.7, (0, 255, 0),
2)
    # cv2.imshow("cropped", cropped)
    cv2.imshow("Output", crop_img)
    cv2.waitKey(0)


def result():
    import warnings
    warnings.filterwarnings('ignore')




def main_account_screen():
    global main_screen
    main_screen = Tk()
```

```
    width = 600
    height = 600
    screen_width = main_screen.winfo_screenwidth()
    screen_height = main_screen.winfo_screenheight()
    x = (screen_width / 2) - (width / 2)
    y = (screen_height / 2) - (height / 2)
    main_screen.geometry("%dx%d+%d+%d" % (width, height, x, y))
    main_screen.resizable(0, 0)
    # main_screen.geometry("300x250")
    main_screen.configure(bg='cyan')
    main_screen.title("DeepFake  Detection  ")

    Label(text="DeepFake Detection", width="300", height="5", bg='cyan', font=("Calibri",
16)).pack()

    Button(text="Training", font=(
        'Verdana', 15), height="2", width="30", command=fulltraining, highlightcolor="black",
bg='cyan').pack(side=TOP)

    Label(text="").pack()
    Button(text="Image", font=(
        'Verdana', 15), height="2", width="30", bg='cyan', command=image).pack(side=TOP)

    Label(text="").pack()
    Button(text="Video", font=(
        'Verdana', 15), height="2", width="30", bg='cyan', command=testing).pack(side=TOP)

    Label(text="").pack()

    main_screen.mainloop()


main_account_screen()
```

NEWDENSEMODEL.PY

```
import os
import cv2
import json
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sn
import pandas as pd
from tensorflow.keras.preprocessing.image import ImageDataGenerator, img_to_array,
load_img
from tensorflow.keras.utils import to_categorical
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from tensorflow.keras.callbacks import ReduceLROnPlateau, EarlyStopping
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import os
import random
import glob  # to find files

# Seaborn library for bar chart
import seaborn as sns

# Libraries for TensorFlow
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.preprocessing import image
from tensorflow.keras import models, layers



input_shape = (128, 128, 3)
data_dir = 'dataset'
```

```
real_data = [f for f in os.listdir(data_dir+'/real') if f.endswith('.png')]
fake_data = [f for f in os.listdir(data_dir+'/fake') if f.endswith('.png')]

X = []
Y = []

for img in real_data:
    X.append(img_to_array(load_img(data_dir+'/real/'+img)).flatten() / 255.0)
    Y.append(1)
for img in fake_data:
    X.append(img_to_array(load_img(data_dir+'/fake/'+img)).flatten() / 255.0)
    Y.append(0)

Y_val_org = Y

#Normalization
X = np.array(X)
Y = to_categorical(Y, 2)

#Reshape
X = X.reshape(-1, 128, 128, 3)

#Train-Test split
X_train, X_val, Y_train, Y_val = train_test_split(X, Y, test_size = 0.2, random_state=5)

from keras.models import Model
from keras.layers import Conv2D, MaxPooling2D, Dense, Input, Activation, Dropout,
GlobalAveragePooling2D, \
    BatchNormalization, concatenate, AveragePooling2D
#from keras.optimizers import Adam

from tensorflow.keras import optimizers

def conv_layer(conv_x, filters):
```

```
    conv_x = BatchNormalization()(conv_x)
    conv_x = Activation('relu')(conv_x)
    conv_x = Conv2D(filters, (3, 3), kernel_initializer='he_uniform', padding='same',
use_bias=False)(conv_x)
    conv_x = Dropout(0.2)(conv_x)
    return conv_x


def dense_block(block_x, filters, growth_rate, layers_in_block):
    for i in range(layers_in_block):
        each_layer = conv_layer(block_x, growth_rate)
        block_x = concatenate([block_x, each_layer], axis=-1)
        filters += growth_rate
    return block_x, filters


def transition_block(trans_x, tran_filters):
    trans_x = BatchNormalization()(trans_x)
    trans_x = Activation('relu')(trans_x)
    trans_x = Conv2D(tran_filters, (1, 1), kernel_initializer='he_uniform', padding='same',
use_bias=False)(trans_x)
    trans_x = AveragePooling2D((2, 2), strides=(2, 2))(trans_x)

    return trans_x, tran_filters


def dense_net(filters, growth_rate, classes, dense_block_size, layers_in_block):
    input_img = Input(shape=(128, 128, 3))
    x = Conv2D(24, (3, 3), kernel_initializer='he_uniform', padding='same',
use_bias=False)(input_img)

    dense_x = BatchNormalization()(x)
    dense_x = Activation('relu')(x)
```

```
    dense_x = MaxPooling2D((3, 3), strides=(2, 2), padding='same')(dense_x)
    for block in range(dense_block_size - 1):
        dense_x, filters = dense_block(dense_x, filters, growth_rate, layers_in_block)
        dense_x, filters = transition_block(dense_x, filters)

    dense_x, filters = dense_block(dense_x, filters, growth_rate, layers_in_block)
    dense_x = BatchNormalization()(dense_x)
    dense_x = Activation('relu')(dense_x)
    dense_x = GlobalAveragePooling2D()(dense_x)

    output = Dense(classes, activation='softmax')(dense_x)

    return Model(input_img, output)

dense_block_size = 3
layers_in_block = 4

growth_rate = 12
classes = 2
model = dense_net(growth_rate * 2, growth_rate, classes, dense_block_size,
layers_in_block)
model.summary()



model.compile(loss='binary_crossentropy',
            optimizer=optimizers.Adam(lr=1e-5, beta_1=0.9, beta_2=0.999, epsilon=None,
decay=0.0, amsgrad=False),
            metrics=['accuracy'])

#Currently not used
early_stopping = EarlyStopping(monitor='val_loss',
                               min_delta=0,
                               patience=2,
                               verbose=0, mode='auto')
```

```
EPOCHS = 5
BATCH_SIZE = 100
history = model.fit(X_train, Y_train, batch_size = BATCH_SIZE, epochs = EPOCHS,
validation_data = (X_val, Y_val), verbose = 1)
model.save('deepfake-detection-model.h5')
f, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 4))
t = f.suptitle('Pre-trained InceptionResNetV2 Transfer Learn with Fine-Tuning & Image
Augmentation Performance ', fontsize=12)
f.subplots_adjust(top=0.85, wspace=0.3)

epoch_list = list(range(1,EPOCHS+1))
ax1.plot(epoch_list, history.history['accuracy'], label='Train Accuracy')
ax1.plot(epoch_list, history.history['val_accuracy'], label='Validation Accuracy')
ax1.set_xticks(np.arange(0, EPOCHS+1, 1))
ax1.set_ylabel('Accuracy Value')
ax1.set_xlabel('Epoch #')
ax1.set_title('Accuracy')
l1 = ax1.legend(loc="best")
plt.show()
ax2.plot(epoch_list, history.history['loss'], label='Train Loss')
ax2.plot(epoch_list, history.history['val_loss'], label='Validation Loss')
ax2.set_xticks(np.arange(0, EPOCHS+1, 1))
ax2.set_ylabel('Loss Value')
ax2.set_xlabel('Epoch #')
ax2.set_title('Loss')
l2 = ax2.legend(loc="best")

plt.show()import os
import cv2
import json
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sn
```

```
import pandas as pd
from tensorflow.keras.preprocessing.image import ImageDataGenerator, img_to_array,
load_img
from tensorflow.keras.utils import to_categorical
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from tensorflow.keras.callbacks import ReduceLROnPlateau, EarlyStopping
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import os
import random
import glob  # to find files

# Seaborn library for bar chart
import seaborn as sns

# Libraries for TensorFlow
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.preprocessing import image
from tensorflow.keras import models, layers



input_shape = (128, 128, 3)
data_dir = 'dataset'

real_data = [f for f in os.listdir(data_dir+'/real') if f.endswith('.png')]
fake_data = [f for f in os.listdir(data_dir+'/fake') if f.endswith('.png')]

X = []
Y = []

for img in real_data:
    X.append(img_to_array(load_img(data_dir+'/real/'+img)).flatten() / 255.0)
```

```
    Y.append(1)
for img in fake_data:
    X.append(img_to_array(load_img(data_dir+'/fake/'+img)).flatten() / 255.0)
    Y.append(0)

Y_val_org = Y

#Normalization
X = np.array(X)
Y = to_categorical(Y, 2)

#Reshape
X = X.reshape(-1, 128, 128, 3)

#Train-Test split
X_train, X_val, Y_train, Y_val = train_test_split(X, Y, test_size = 0.2, random_state=5)

from keras.models import Model
from keras.layers import Conv2D, MaxPooling2D, Dense, Input, Activation, Dropout,
GlobalAveragePooling2D, \
    BatchNormalization, concatenate, AveragePooling2D
#from keras.optimizers import Adam

from tensorflow.keras import optimizers

def conv_layer(conv_x, filters):
    conv_x = BatchNormalization()(conv_x)
    conv_x = Activation('relu')(conv_x)
    conv_x = Conv2D(filters, (3, 3), kernel_initializer='he_uniform', padding='same',
use_bias=False)(conv_x)
    conv_x = Dropout(0.2)(conv_x)
    return conv_x
```

```
def dense_block(block_x, filters, growth_rate, layers_in_block):
    for i in range(layers_in_block):
        each_layer = conv_layer(block_x, growth_rate)
        block_x = concatenate([block_x, each_layer], axis=-1)
        filters += growth_rate
    return block_x, filters


def transition_block(trans_x, tran_filters):
    trans_x = BatchNormalization()(trans_x)
    trans_x = Activation('relu')(trans_x)
    trans_x = Conv2D(tran_filters, (1, 1), kernel_initializer='he_uniform', padding='same',
use_bias=False)(trans_x)
    trans_x = AveragePooling2D((2, 2), strides=(2, 2))(trans_x)

    return trans_x, tran_filters


def dense_net(filters, growth_rate, classes, dense_block_size, layers_in_block):
    input_img = Input(shape=(128, 128, 3))
    x = Conv2D(24, (3, 3), kernel_initializer='he_uniform', padding='same',
use_bias=False)(input_img)

    dense_x = BatchNormalization()(x)
    dense_x = Activation('relu')(x)

    dense_x = MaxPooling2D((3, 3), strides=(2, 2), padding='same')(dense_x)
    for block in range(dense_block_size - 1):
        dense_x, filters = dense_block(dense_x, filters, growth_rate, layers_in_block)
        dense_x, filters = transition_block(dense_x, filters)

    dense_x, filters = dense_block(dense_x, filters, growth_rate, layers_in_block)
    dense_x = BatchNormalization()(dense_x)
    dense_x = Activation('relu')(dense_x)
```

```
    dense_x = GlobalAveragePooling2D()(dense_x)

    output = Dense(classes, activation='softmax')(dense_x)

    return Model(input_img, output)

dense_block_size = 3
layers_in_block = 4

growth_rate = 12
classes = 2
model = dense_net(growth_rate * 2, growth_rate, classes, dense_block_size,
layers_in_block)
model.summary()



model.compile(loss='binary_crossentropy',
          optimizer=optimizers.Adam(lr=1e-5, beta_1=0.9, beta_2=0.999, epsilon=None,
decay=0.0, amsgrad=False),
          metrics=['accuracy'])

#Currently not used
early_stopping = EarlyStopping(monitor='val_loss',
                       min_delta=0,
                       patience=2,
                       verbose=0, mode='auto')
EPOCHS = 5
BATCH_SIZE = 100
history = model.fit(X_train, Y_train, batch_size = BATCH_SIZE, epochs = EPOCHS,
validation_data = (X_val, Y_val), verbose = 1)
model.save('deepfake-detection-model.h5')
f, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 4))
t = f.suptitle('Pre-trained InceptionResNetV2 Transfer Learn with Fine-Tuning & Image
Augmentation Performance ', fontsize=12)
```

```
f.subplots_adjust(top=0.85, wspace=0.3)

epoch_list = list(range(1,EPOCHS+1))
ax1.plot(epoch_list, history.history['accuracy'], label='Train Accuracy')
ax1.plot(epoch_list, history.history['val_accuracy'], label='Validation Accuracy')
ax1.set_xticks(np.arange(0, EPOCHS+1, 1))
ax1.set_ylabel('Accuracy Value')
ax1.set_xlabel('Epoch #')
ax1.set_title('Accuracy')
l1 = ax1.legend(loc="best")
plt.show()
ax2.plot(epoch_list, history.history['loss'], label='Train Loss')
ax2.plot(epoch_list, history.history['val_loss'], label='Validation Loss')
ax2.set_xticks(np.arange(0, EPOCHS+1, 1))
ax2.set_ylabel('Loss Value')
ax2.set_xlabel('Epoch #')
ax2.set_title('Loss')
l2 = ax2.legend(loc="best")

plt.show()
```

APPENDIX B

SCREENSHOTS

Sample Output

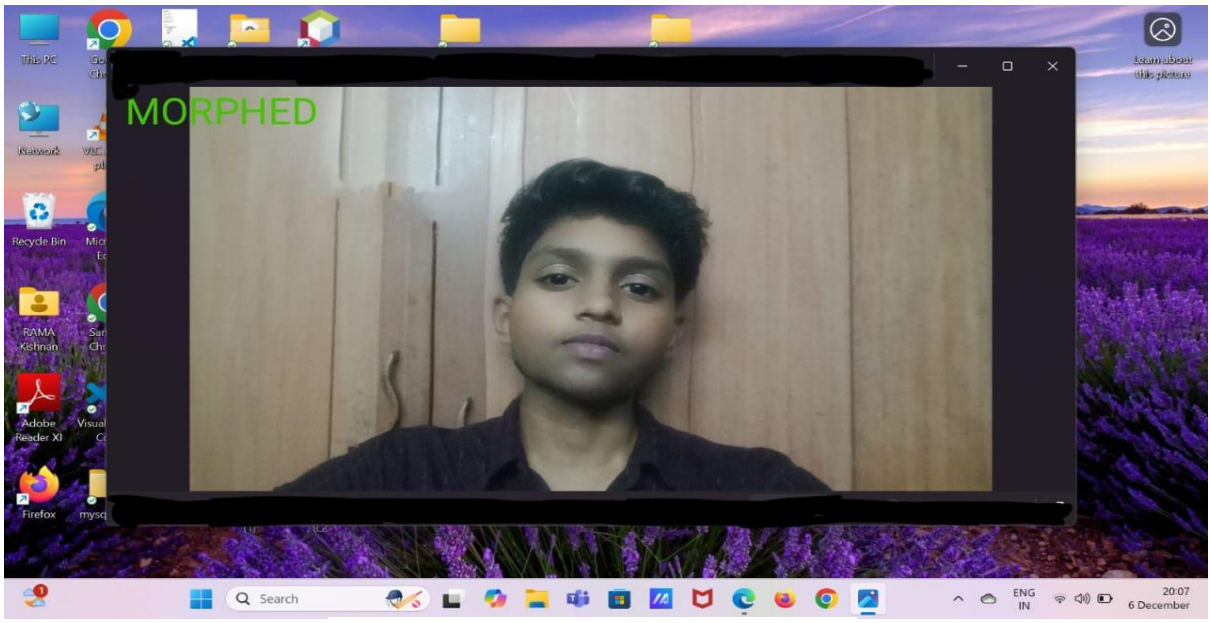

FIGURE 1

FIGURE 2

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