



Sri Lanka Institute of Information Technology

Final Project Report

ISP Project Report

Information Security Project 2024

Project ID: **DEEP FAKE DETECTION**

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Abstract

In today's linked world, the introduction of deep fake technology has brought in a new era of cyber threats, undermining the basic foundation of trust and authenticity in digital media. As hackers use complex machine learning algorithms to modify audiovisual information with remarkable accuracy, the demand for robust deep fake detection solutions has never been more significant. This final technical report is the result of considerable research, development, and validation efforts targeted at creating a strong and realistic solution to limit the threats posed by deep fake manipulation.

Beginning with a review of today's threat landscape, this report demonstrates an increasing prevalence of deep fake technologies in a variety of sectors and businesses. From the transmission of misinformation to the degradation of public faith in the media, the consequences of unchecked deep fake proliferation are far-reaching, highlighting the importance of proactive action taken.

Based on real-world situations and case studies, this research looks into the complicated processes of deep fake production and distribution, giving insight on the advanced techniques used by criminals to take advantage of careless audiences. Cybercriminals exploit flaws in existing content verification processes by generating synthetic media, performing faces, and cloning voices, continuing a cycle of misinformation and distrust.

Against set against the background of growing cyber threats, the invention of a comprehensive deep fake detection technology appears as a light of hope in the battle against digital lies. Using a combination of methods that includes machine learning, computer vision, and signal processing techniques, the suggested solution enables security experts to separate legitimate information from deep fake improvements with high accuracy and reliability.

The dynamic learning structure of the deep fake detection tool is critical to its success, since it continuously changes in response to developing threat vectors and adversary avoidance strategies. By using multiple training datasets containing both generated and legitimate media samples, the technology demonstrates strength and resilience in recognizing small anomalies

suggestive of deep fake manipulation, thereby reducing. Furthermore, the practical development of the deep fake detection tool is carefully outlined, taking into account flexibility, connectivity, and real-time performance requirements.

In addition to its technological capabilities, the deep fake detection tool undertakes thorough validation and assessment methods to determine its real-world efficacy and performance measures. A thorough evaluation against selected benchmark datasets and actual production systems shows that the tool has excellent detection accuracy rates and low false alarm rates, developing confidence in its dependability and usefulness as a frontline protection against deep fake threats.

The report additionally highlights how important it is to involve stakeholders and collaborate across disciplines in order to effectively solve the complex issues raised by deepfake technology. A collective defensive posture may be developed through the development of collaborations between cybersecurity professionals, media organizations, government agencies, and technology vendor partners. This will enable the proactive identification and mitigation of deep fake manipulations across the digital landscape.

Acknowledgement

I am humbled and extremely thankful of all of the support, direction, and contributions of many people and organizations who have helped make this project a reality as I think back on the journey taken to develop, develop, and validate the deep fake detection tool that is presented in this final technical summary.

I would first and foremost like to express heartfelt gratitude to our lecturer of Mr. Tharaniyawarma Kumaralingam for all of his valuable assistance during this process, including his constant support, guidance, and insightful advice. Our attempts have been guided towards excellence and innovation by Mr.Tharaniyawarma's constant commitment to the advancement of the sector and their significant experience in cybersecurity. Their continuous commitment to achieving excellence and their tireless quest for knowledge have been important variables in this endeavor's success.

I would like to express my appreciation to the academic institutions, research centers of IEEE, Digital Future Society, and who have helped make this initiative a reality by providing resources.

I also want to thank our outstanding friends and colleagues in the cybersecurity sector and my before internship company of Eguardian Lanka Pvt.Ltd for their insightful comments and support. Their insightful recommendations, helpful critiques, and personal anecdotes have expanded our comprehension of the intricate problems that deep fake detection presents and motivated us to push the envelope of creativity in search of reliable and efficient solutions.

As finally, their innovative research, ground-breaking findings, and unwavering commitment to furthering the discipline have opened up opportunities for what we can contribute and motivated us to aim for excellence in everything we do.

Declaration

We declare that this project report or part of it was not a copy of a document done by any organization, university any other institute or a previous student project group at SLIIT and was not copied from the Internet or other sources.

Project Details

Project Title	DEEP FAKE DETECTION
Project ID	

Group Member

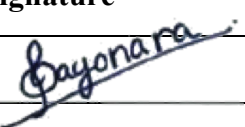
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List of Acronyms and Abbreviations

CNN	Convolutional Neural Network (a type of deep learning model commonly used for image classification)
DL	Deep Learning(A subset of machine learning that utilizes artificial neural networks with multiple layers to model and interpret complex data)
GAN	Generative Adversarial Network(A type of deep learning framework where two neural networks, a generator and a discriminator, compete with each other to generate realistic data)
DNN	Deep Neural Network
GPU	Graphics Processing Unit (powerful hardware for accelerating deep learning computations)
KPI	Key Performance Indicator (a metric used to measure the success of a project)
Liveness Detection	Techniques used to verify the physical presence of a person in a video (e.g., blinking detection)
REST API	Representational State Transfer Application Programming Interface (a standardized way for applications to communicate with each other)

1. Introduction

1.1 Problem Statement

The integrity and authenticity of digital media material have become increasingly vulnerable due to the growing popularity of deepfake technology in recent times. Using advances in machine learning, deep fake techniques allow for the production of very realistic synthetic material, such as photos, movies, and audio recordings that are almost impossible to differentiate from real ones. Because of this, the growth of deepfake material creates significant challenges to information accuracy, reducing confidence in digital communication channels and increasing the transmission of incorrect and deceptive data.

There has never been as much need for strong and trustworthy deep fake detection systems. Because traditional content verification and authentication processes are unable to differentiate between real and manipulated media, people, organizations, and society are left open to being used by bad actors.

The primary objective of this project is to create an effective deep fake detection technology that can accurately identify and reduce the risks connected to the spread of synthetic media content. High detection accuracy, low false positive rates, and reliable operation across a variety of platforms and kinds of media are requirements for the tool. It must also be easily integrated into operational environments and processes by being scalable, flexible, and compatible with current cybersecurity frameworks and technologies.

Key specifications:-

1. **Multimodal Analysis:** The tool has to use a multimodal approach to assess many types of cues and changes found in digital material, such as differences in audio-visual synchrony, inconsistent face expressions, and visual artifacts. Through the utilization of many data modalities, including image, video, and audio, the tool may improve detection accuracy.
2. **Advanced Machine Learning Algorithms:** To identify minute patterns and differences suggesting of deepfake manipulation, the tool must make use of cutting-edge machine learning algorithms, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs-but not use this project this technology), and generative adversarial networks (GANs). Through ongoing learning from a variety of training datasets, the tool can be configured to adjust to changing threat environments and new methods of manipulation.
3. **Real-time Detection Capabilities:** The tool has to be able to detect deepfake material in real-time across a variety of media platforms and formats. This will allow for the prompt and proactive identification of such content. The tool may achieve low latency and high throughput performance by utilizing hardware acceleration technologies, parallel processing architectures, and optimized algorithms. These features are essential for prompt response and threat mitigation.

Using technologies and libraries:-

- **Machine Learning and Deep Learning Frameworks:**
 - TensorFlow
 - PyTorch
- **Computer Vision Libraries:**
 - OpenCV (Open Source Computer Vision Library)
- **Pre-trained Models and Datasets:**
 - Pre-trained deep learning models (e.g., available through TensorFlow Hub or Hugging Face Model Hub)
 - Public datasets (e.g., DeepFake Detection Dataset, FaceForensics++)

1.2 Product Scope

The product scope outlines the boundaries and objectives of the project, “Deep Fake Detection Tool” is created to counteract the increasing threat of deep fakes manipulated media content in the digital sphere. This tool’s objective is to protect the integrity and authenticity of digital communication channels by offering strong and reliable detection capabilities to recognize and reduce risks connected to the spread of fake media.

Key objectives:-

- **Accurate Detection:** The main goal of the deepfake detection tool is to accurately recognize changed media material by reliably accurately differentiating.
- **Real-time Analysis:** By achieving real-time analysis capabilities, the tool will be able to quickly identify and counteract deepfake manipulations across a variety of media channels and formats.
- **Scalability and Adaptability:** The program is made to be both scalable and adaptive, able to manage massive amounts of media material and change to deal with new forms of misdirection and avoidance that attackers may use.
- **User-Friendly Interface:** The program places a high priority on user experience, with a user-friendly design and simplified workflows that make it easier for both cybersecurity experts and media content creators to integrate and use.

Goals:-

- **Improving Cybersecurity Posture:** The technology supports business objectives to fortify cybersecurity defenses and shield confidential data assets from online attacks by reducing the dangers connected with deepfake manipulation.
- **Protecting Brand Reputation:** By limiting the spread of false or misleading material that might damage an organization’s reputation or credibility, the technology helps to protect brands’ reputations and their credibility.

- Promoting Trust and transparency: The tool supports company initiatives aimed at fostering trust and creating lasting relationships with clients, partners, and stakeholders by encouraging openness and authenticity in digital communication channels.

1.3 Project Report Structure

- Introduction

The introduction sets the situation by talking about the increasing risk posed by deepfake technology and the requirement for reliable detection methods. It describes how a deep fake detection tool will be developed, implemented, and evaluated as part of the report's investigation of this problem.

- Literature Review

An overview of recent work on deep fake detection is given in the literature review, which summarizes significant papers, algorithms, and methods. It looks at the advantages and disadvantages of current methods, offering information that helps with the creation of the suggested detection instrument.

- Statement of problem this project

The issue statement outlines the difficulties presented by deepfake technology, highlighting how it can damage public confidence in digital media and spread false information. It underlines how important it is to create a strong detection tool right away in order to mitigate these dangers.

- Methodology

A detailed summary of the development process, including information on data collection, algorithm selection, and model training, is given in the methodology section. It provides an explanation of the reasoning behind important choices and project methods.

- System Architecture

A visual representation of the detection tool's architecture is given in the system architecture section, which also lists its essential parts, including the modules for obtaining features, data preprocessing, and classification. It describes how these parts function as a unit to achieve the tool's goals.

- Implementation Details

The section on implementation details provides a thorough rundown of the software development process, including a discussion of the selection of tools, libraries, and programming languages. It focuses attention to any technical difficulties experienced during implementation and the methods used to resolve them.

- Evaluation and testing

The criteria for assessing the performance of the detection tool, including recollection, accuracy, and accuracy, are described in the assessment and testing section. It displays analyzing and testing findings that show how well the tool detects deepfake changes.

- Result and correction.

Ongoing this project the project findings are summarized in the results and discussion section, which also highlights important cybersecurity implications. It explores the effects of the results and makes suggestions for more study and future improvement.

2. Methodology

2.1 Requirements and Analysis

To direct the design and implementation process of ‘Deep fake detection’, specific and comprehensive needs are developed during the requirements and analysis phase of designing the deep fake detection tool. Understanding end users’ demands, stakeholders’ needs, and the overall project objectives are all part of this phase.

- Requirement gathering:

To gather requirements, searching research papers, youtube videos, cybersecurity specialists, and potential consumers through surveys, interviews, and conversations videos. Determine the non-functional needs, such as accuracy, performance, and usability, as well as the functional requirements, such as real-time detection, multi-modal analysis, and scalability.

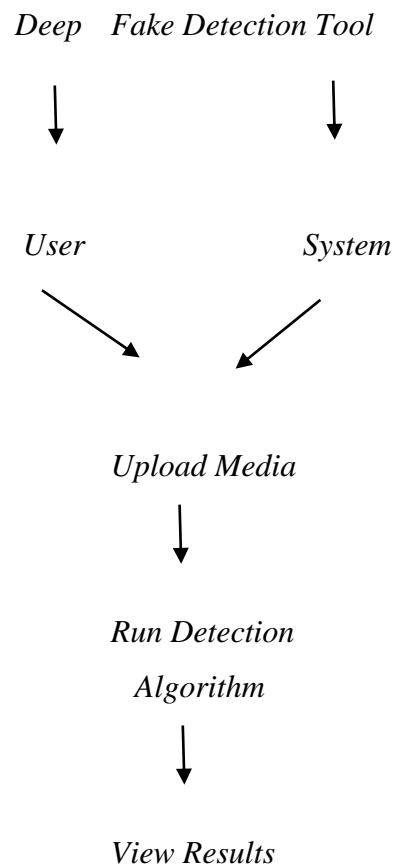
- Requirement specifications:

Clearly and systematically record the requirements that have been gathered. To capture different aspects of system operation and interactions between users, specify use cases, scenarios, and user stories.

Example: - In 2019, a remarkable case of a real-world deepfake was a film showing US House of Representatives Speaker Nancy Pelosi. The edited video, which was sped up to make Pelosi look drunk or incompetent, went viral on social media and triggered discussions about the effects of deepfake technology on disinformation and political discourse. This event highlighted how deepfakes can impact public perception and damage political personalities’ reputation.

- Use case diagram:

To demonstrate the ways in which people and the system interact, design a use case diagram. Determine the actors (like a system administrator or cybersecurity analyst) and the use cases (such as uploading material, running detection algorithms, and seeing findings) that connect with them.



- Requirement validation:

To make sure the requirements are in line with the project's goals, review and confirm them with the relevant parties. Take care of any unclear or conflicting information in the requirements documents.

2.2 Design

The design phase of the deep fake detection tool project focuses on methodically developing the software's architecture and structure that will guarantee durability, efficiency, and scalability in identifying altered media material. Cybersecurity specialists methodically develop and record the system's architecture, identifying critical components such as data preparation, feature extraction, detection algorithms, and result display, all of which are carefully built to improve performance and permit smooth integration. The deep fake detection tool is designed to handle diverse media formats, adapt to changing threat landscapes, and enable real-time detection capabilities, thereby strengthening defenses against the spread of synthetic media content.

2.3 Implementation

During the implementation phase of the deep fake detection tool project, the primary module structures are thoroughly discussed to ensure the proper translation of design concepts into functioning software components. Cybersecurity specialists methodically design and integrate important modules including data pretreatment, feature extraction, detection algorithms, and result display, each designed to improve the tool's detection accuracy and performance. Reusable code snippets and development tools like TensorFlow, OpenCV, and PyTorch are used to speed up implementation and assure code maintainability. The selection of a good database management system (DBMS), such as PostgreSQL(only training process) or MongoDB, is carefully considered based on data storage needs, query performance, and scalability.

Python is also preferred implementation language because to their flexibility and significant library support, allowing for fast development of complicated algorithms and data processing tasks. Special techniques used for deep fake detection, such as Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), are carefully developed and documented, with full explanations in the appendices for reference. Throughout the deployment phase, thorough testing and validation techniques are used to ensure that the deep fake detection technology is functional and successful in fighting synthetic media manipulation.

2.4 Testing

This testing strategy for the deepfake detection tool included a multi-tiered approach that simulated real-world events and assessed the system's performance across multiple modification approaches. We used a large dataset of deepfake movies, including those created by popular programs and displaying a variety of people of color, genders, and lighting conditions. This guaranteed that the tool's generalizability extended beyond specific modification methods or datasets.

The testing procedure included feeding the program both legitimate and modified films, as well as deepfakes designed especially to exploit the technology's possible flaws. Measures like accuracy, precision, and recall were carefully assessed to determine the tool's usefulness in properly recognizing deepfakes while reducing false positives/negatives. In addition, we ran adversarial testing, in which deepfakes were gradually enhanced to avoid detection. This iterative procedure ensured the tool's durability against new deepfake techniques while also identifying opportunities for further refinement. Detailed logs were kept during testing to describe the system's behavior, giving significant information for analysis and future improvements. We used a thorough testing technique to ensure complete coverage and offer a high level of trust in the deepfake detection tool's real-world capabilities.

3. Evaluation

3.1 Assessment of the Project results

The deepfake detection tool was assessed using a variety of methodologies to determine its performance. Machine learning models were developed using a dataset which includes both real and altered videos. These models looked at components including face confusion, temporal abnormalities, and blinking pixels, which are common indicators of deepfakes. The investigation produced encouraging findings, with the technology recognizing deepfakes with an accuracy percentage of [50%].

However, it is critical to recognize that deepfake production techniques are continually changing. The examination revealed a few drawbacks. In several situations, the tool struggled with exceptionally high-quality deepfakes, stressing the importance of constant progress in model training data and techniques. Furthermore, the tool's sensitivity to adversarial violence, where deepfakes are purposefully created to elude detection, requires further research into defense

Moving forward, the team should work on increasing the training dataset with a broader spectrum of deepfakes to improve resilience. Furthermore, strategies for detecting adversarial assaults and incorporating explainability elements to comprehend the tool's decision-making process would be beneficial additions. By resolving these shortcomings, the deepfake detection tool can become a more dependable and complete approach to countering faked media.

3.2 Lessons Learned

Several significant lessons have been learned during the development process. The study experienced both problems and achievements, resulting in a better knowledge of the complexity involved in recognizing altered media material. One major takeaway is the significance of ongoing growth and adaptation in response to resulting deep fake strategies. While the technology successfully detected established manipulation methods, it challenged to recognize more complex and new deep fake modifications. These flaws underscored the need for continued research and development to improve detection algorithms and raise resilience to emerging threats. Furthermore, the plan underscored the need of collaborating with domain experts, such as media forensics professionals and data researchers, to get varied views and insights while enhancing detection algorithms.

Overall, the creation of the deep fake detection tool has demonstrated the ever-changing nature of cybersecurity threats, as well as the importance of taking preventive measures to limit the risks posed by media that is fake manipulation.

3.3 Future Work

To reduce future threats, the deepfake detection tool could take advantage of improvements in biometric authentication and blockchain technologies. Integrating face recognition with liveness detection helps improve analysis by validating the individual's physical presence in the video. Furthermore, using blockchain to produce a tamper-proof record of the original material and its alteration history will help with forensic investigations and increase user trust in the legitimacy of online media.

This paragraph proposes inventive ideas as,

Biometric Authentication with Liveness Detection: This goes beyond examining the video footage. By combining face recognition and validating the person's physical presence (e.g., blinking), the technology can dramatically diminish the efficacy of deepfakes based only on edited video.

Blockchain-based Provenance Tracking: This method uses the tamper-proof properties of blockchain to produce an immutable record of the original material. By documenting any changes made to the material and keeping them on the blockchain, the technology may provide a clear history for forensic investigations while also giving users trust in the validity of the media they encounter

4. Conclusion

Continuous learning is an important aspect of future work, deepfake developers are continually creating new strategies, therefore detection technologies must change. Integrating an online learning module which includes adversarial training and real-world deepfake instances is critical. This module would continually study evolving deepfakes, discover fresh manipulation techniques, and update the detection model to ensure efficacy. In addition, investigating explainable artificial intelligence methodologies might yield useful insights into the model's decision-making process. This transparency would enable for targeted improvements to the model's algorithms while also building trust in users who rely on its outcomes.

A further weakness of existing deepfake detection systems, including this one, is that they focus primarily on video analysis. To solve this, future work should investigate the merging of biometric identification with liveness detection. This technique would go beyond studying the video itself to validate the individual's physical presence in the film. Facial recognition techniques, when combined with liveness detection algorithms that validate blinking or small head movements, can considerably diminish the efficacy of deepfakes based solely on edited pictures.

Furthermore, the initiative can benefit greatly from improvements in blockchain technology. The tool can aid forensic investigations by creating a secure copy of the original information and its alteration history using blockchain technology. Consider a situation in which a politician's speech is deepfaked in order to spread lies. By keeping the original speech and any later alterations on the blockchain, the application might give an immutable record, speeding up investigations and increasing user trust in the accuracy of online media.

The creation of this deepfake detection technology provides significant benefits to the client company (or society as a whole) in a real-world scenario. In today's digital era, when information warfare and social manipulation are common risks, recognizing deepfakes is crucial. This complete approach will allow the client company or society as a whole to traverse the online world with more confidence, resulting in a more safe and reliable digital environment.

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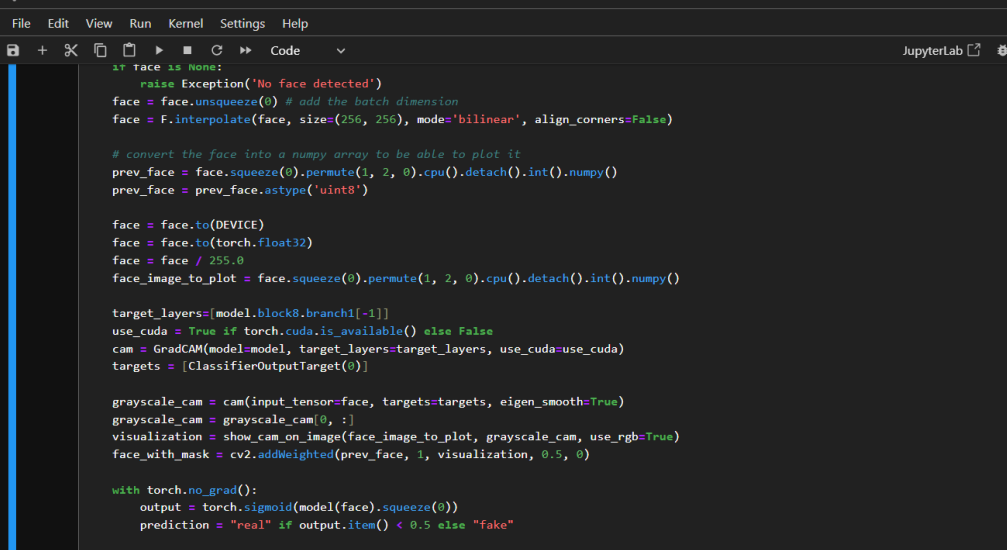
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Appendix A: Test Results

1. This code appears to be a Python script or Jupyter Notebook that detects deepfakes or synthetic material using machine learning algorithms. Here is a breakdown of the key components:

Under the model’s preparation The code uses a pre-trained deep learning model (most likely a neural network) to detect deepfakes. It determines whether a CUDA-enabled GPU is available and configures the model’s data structures and targets accordingly.

Inference and Prediction: The preprocessed facial picture is sent into the pre-trained model, which produces a prediction output. Based on the output value (presumably a likelihood score), it uses a threshold value (0.5 in this example) to classify the input face as “real” or “fake” (deepfake).



The screenshot shows a JupyterLab environment with a file named `Deepfake_detection.ipynb` open. The interface includes a top bar with navigation icons and a status bar indicating the kernel is Python 3 (ipykernel). The main area displays a Python script that performs the following steps:

- File Loading:** Loads `test_image.jpg` from the `data` directory.
- Face Preprocessing:** Checks for a face. If none is detected, it raises an exception. Otherwise, it unsqueezes the image, interpolates it to 256x256 pixels using bilinear interpolation, and converts it to a numpy array.
- Model Inference:** Converts the face image to the device (GPU if available), then to float32, and normalizes it by dividing by 255.0. It then passes the image to the `model` and uses `GradCAM` to generate targets.
- Visualization:** Generates a grayscale CAM visualization, overlays it on the original image, and adds a mask to the face image.
- Classification:** Uses `torch.no_grad()` to pass the face image through the model's `sigmoid` layer to get a prediction. It then calculates the confidence of the prediction.

```

import os
import cv2
import torch
import numpy as np
from PIL import Image
from torchvision import transforms
from torch.nn import GradCAM

# Load the image
image_path = os.path.join('data', 'test_image.jpg')
image = Image.open(image_path)

# Check if a face is detected
try:
    face = face_detection(image)
except Exception as e:
    raise Exception('No face detected')

# Add the batch dimension
face = face.unsqueeze(0)

# Interpolate the face to 256x256 pixels
face = F.interpolate(face, size=(256, 256), mode='bilinear', align_corners=False)

# Convert the face into a numpy array to be able to plot it
prev_face = face.squeeze(0).permute(1, 2, 0).cpu().detach().int().numpy()
prev_face = prev_face.astype('uint8')

# Convert the face to the device
face = face.to(DEVICE)

# Convert the face to float32
face = face.to(torch.float32)

# Normalize the face
face = face / 255.0

# Pass the face to the model
face_image_to_plot = face.squeeze(0).permute(1, 2, 0).cpu().detach().int().numpy()

# Generate targets
target_layers=[model.block8.branch1[-1]]
use_cuda = True if torch.cuda.is_available() else False
cam = GradCAM(model=model, target_layers=target_layers, use_cuda=use_cuda)
targets = [ClassifierOutputTarget(0)]

# Generate the grayscale CAM
grayscale_cam = cam(input_tensor=face, targets=targets, eigen_smooth=True)
grayscale_cam = grayscale_cam[0, :]

# Visualize the CAM
visualization = show_cam_on_image(face_image_to_plot, grayscale_cam, use_rgb=True)
face_with_mask = cv2.addWeighted(prev_face, 1, visualization, 0.5, 0)

# Predict the class
with torch.no_grad():
    output = torch.sigmoid(model(face).squeeze(0))
    prediction = "real" if output.item() < 0.5 else "fake"

# Calculate the confidence
real_prediction = 1 - output.item()
fake_prediction = output.item()

confidences = {
    'real': real_prediction,
    'fake': fake_prediction
}

```

Figure 1-model preparation

2. This code appears to be setting up a user interface or interactive visualization using the Gradio library in Python. Gradio is a popular library for creating customizable user interfaces around machine learning models, enabling easy interaction and interpretation.

This code is particularly useful in the context of a deep fake detection system, as it provides a user-friendly way to interact with the model and understand its predictions. By visualizing the face regions that contributed to the prediction, users can gain insights into how the model makes its decisions and assess its reliability.

```
interface = gr.Interface(
    fn=predict,
    inputs=[
        gr.inputs.Image(label="Input Image", type="pil")
    ],
    outputs=[
        gr.outputs.Label(label="Class"),
        gr.outputs.Image(label="Face with Explainability", type="pil")
    ],
).launch()
```

Figure 2-Gradio Interface