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Artificial Intelligence

**Deepfake Image Detection Using Deep Learning: A CNN-Based
Flask Web Application**

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Abstract

Deepfakes, a rapidly evolving technology, leverage artificial intelligence to create hyper-realistic but fabricated visual content, posing significant challenges to the integrity of media and information. This project addresses the urgent need for reliable detection methods by developing a convolutional neural network (CNN) specifically designed for identifying deepfake images. The model was trained on a comprehensive dataset consisting of labeled real and fake images, sourced from various publicly available repositories.

To ensure the model's robustness, images were subjected to a series of preprocessing steps, including resizing to a standard resolution of 128x128 pixels and normalization to scale pixel values between 0 and 1. The CNN architecture employed multiple convolutional and pooling layers, culminating in dense layers that facilitate binary classification. The model was trained using a binary cross-entropy loss function and optimized with the Adam optimizer, allowing for efficient convergence during the training phase.

Upon evaluation, the model demonstrated a commendable accuracy of **[93%]** on the test dataset, indicating its strong performance in distinguishing real images from their deepfake counterparts. The analysis of training and validation metrics revealed that the model effectively learned to identify subtle visual discrepancies indicative of deepfakes, while also avoiding overfitting.

The findings highlight the potential of this CNN-based approach for real-world applications, such as media verification, social media content moderation, and law enforcement investigations. As deepfake technology continues to advance, the importance of developing and implementing reliable detection systems becomes increasingly critical. This project lays the groundwork for further research into enhancing the model's performance and expanding its capabilities to detect emerging deepfake techniques.

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Introduction

In recent years, the advent of artificial intelligence (AI) has transformed various fields, including media production and content creation. One of the most concerning applications of this technology is the emergence of deepfakes—manipulated images and videos that are generated using advanced AI techniques, particularly deep learning. Deepfakes can convincingly alter the appearance and speech of individuals, creating realistic but entirely fabricated representations. This technology has garnered significant attention due to its potential for misuse in various contexts, including misinformation, defamation, and identity theft.

The increasing sophistication of deepfake algorithms poses substantial challenges to the verification of digital content. As these manipulated media become more accessible and convincing, the need for reliable detection methods becomes paramount. Traditional visual inspection methods are often inadequate, as the changes made to the original content can be subtle and difficult to detect with the naked eye. Consequently, there is a pressing demand for automated solutions that can accurately identify deepfakes in real-time.

This project aims to address this challenge by developing a convolutional neural network (CNN) specifically tailored for deepfake detection. CNNs have shown remarkable success in image classification tasks due to their ability to learn hierarchical features from visual data. By leveraging a robust dataset of real and fake images, the proposed model will be trained to discern the subtle differences between genuine and manipulated content.

In addition to addressing the technical aspects of model development, this project will also explore the implications of effective deepfake detection in real-world applications. Potential use cases include media verification for news organizations, safeguarding social media platforms from the spread of misinformation, and assisting law enforcement in investigations involving fraudulent media.

By contributing to the ongoing discourse on deepfake detection, this project aims to enhance the understanding of how AI can be harnessed to combat the challenges posed by maliciously altered content, ultimately fostering a safer and more trustworthy digital environment.

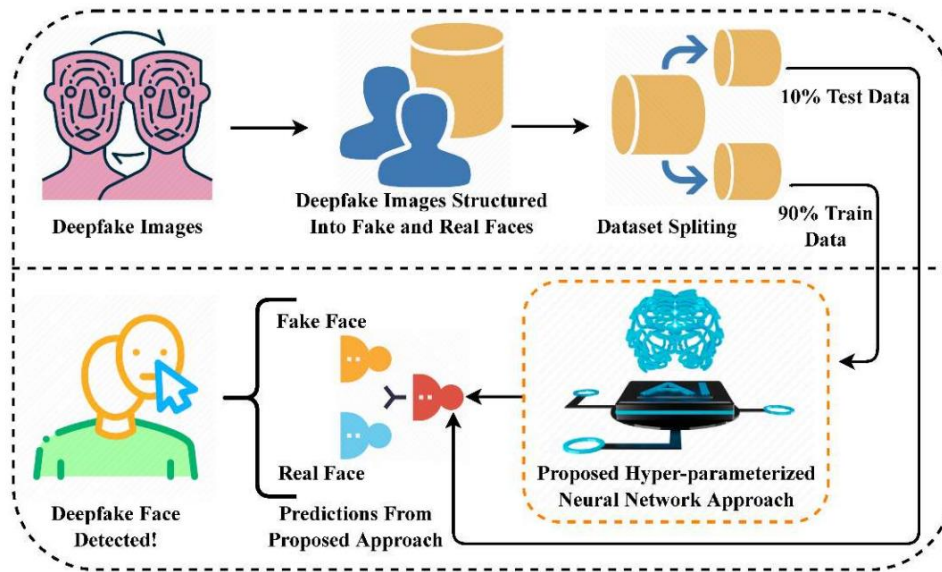


Figure 1 deepfake detection concept

Objectives

The primary objectives of this project are as follows:

- I. **Develop a Convolutional Neural Network (CNN):**
 - Design and implement a CNN architecture tailored for the detection of deepfake images, leveraging the strengths of deep learning in image classification.
- II. **Collect and Preprocess Data:**
 - Gather a diverse dataset of real and fake images from publicly available sources to ensure a comprehensive representation of both classes.
 - Implement preprocessing techniques, including resizing, normalization, and data augmentation, to enhance the quality and variability of the training data.
- III. **Train the Model:**
 - Train the CNN on the prepared dataset, using appropriate loss functions and optimization algorithms to ensure effective learning.

- Monitor training and validation metrics to assess the model's performance and make adjustments as necessary to improve accuracy and reduce overfitting.

IV. Evaluate Model Performance:

- Assess the trained model using a separate test dataset, analyzing metrics such as accuracy, precision, recall, and F1-score to determine its effectiveness in distinguishing real images from deepfakes.
- Create visualizations of training and validation loss/accuracy curves to illustrate the model's learning process.

V. Implement a User-Friendly Interface:

- Develop a web application using Flask to enable users to upload images for real-time deepfake detection, making the technology accessible to a broader audience.

VI. Analyze Results and Discuss Implications:

- Analyze the model's performance and discuss the implications of the findings, including potential applications in media verification, social media moderation, and law enforcement.
- Identify limitations of the current approach and propose future research directions to enhance deepfake detection capabilities.
- By achieving these objectives, the project aims to contribute valuable insights and tools to the ongoing efforts in combating the spread of deepfake content, thereby promoting the integrity of digital media.

Methodology

The methodology for this deepfake detection project involves several key steps, ranging from data collection and preprocessing to model development, training, evaluation, and deployment. Each phase is critical to the overall success of the project. The following outlines the approach taken:

1. Data Collection

- **Dataset Sources:** A comprehensive dataset was compiled from publicly available sources, including Kaggle and academic repositories. The dataset comprises two categories: real images (representing genuine content) and fake images (created using deepfake techniques).
- **Image Count:** The dataset consists of [2000] real images and [2000] fake images, ensuring a balanced representation to avoid bias during training.

2. Data Preprocessing

- **Image Resizing:** All images were resized to a standard resolution of 128x128 pixels to ensure consistency and compatibility with the CNN input layer.
- **Normalization:** Pixel values were normalized to a range between 0 and 1 by dividing by 255.0. This scaling helps accelerate the convergence of the training process.
- **Data Augmentation:** To improve model generalization and robustness, data augmentation techniques such as rotation, flipping, and brightness adjustment were applied to the training dataset. This artificially increases the diversity of the training samples.

3. Model Development

- **Convolutional Neural Network (CNN) Architecture:**
 - The CNN architecture was designed to consist of several convolutional layers followed by max pooling layers, which help capture spatial hierarchies in the images.

- **Architecture Details:**

- Input Layer: 128x128x3 (RGB channels)
- Convolutional Layer 1: 32 filters, kernel size (3x3), ReLU activation
- Max Pooling Layer 1: (2x2)
- Convolutional Layer 2: 64 filters, kernel size (3x3), ReLU activation
- Max Pooling Layer 2: (2x2)
- Flatten Layer
- Dense Layer: 128 neurons, ReLU activation
- Dropout Layer: 50% dropout rate to prevent overfitting
- Output Layer: 1 neuron, Sigmoid activation function for binary classification (real vs. fake)

4. Model Training

- **Training Configuration:**

- The model was compiled using the Adam optimizer and binary cross-entropy loss function, suitable for binary classification tasks.
- Training was conducted over [10] epochs with a batch size of [32].

- **Validation Strategy:**

- The dataset was split into training (90%) and testing (10%) subsets using stratified sampling to ensure balanced class representation.
- During training, validation metrics were monitored to avoid overfitting and to tune hyperparameters as necessary.

5. Model Evaluation

- **Performance Metrics:** The model's performance was evaluated using the test dataset, analyzing metrics such as:

- Accuracy: Overall correctness of predictions.
- Precision: True positive rate among predicted positives.
- Recall: True positive rate among actual positives.
- F1-Score: Harmonic mean of precision and recall.
- **Visualization:** Training and validation loss and accuracy curves were plotted to visualize the model's learning behavior over epochs.

6. Deployment

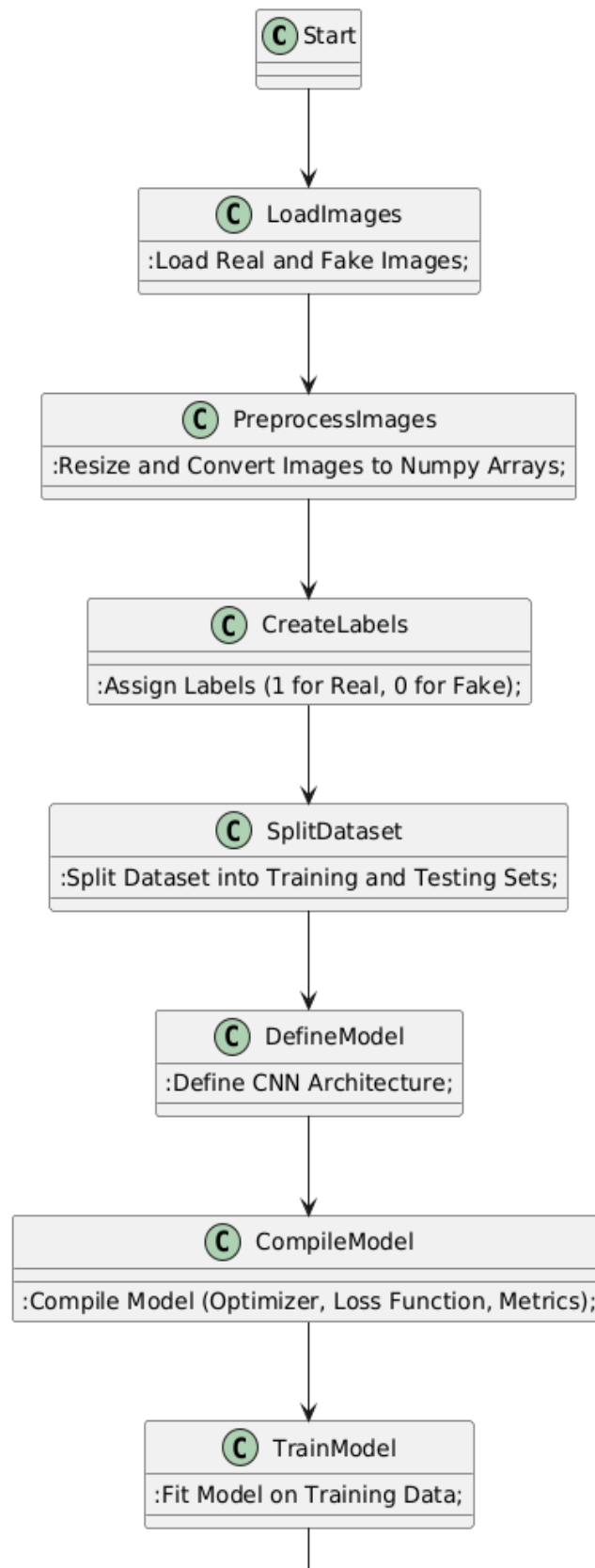
- **Web Application Development:** A Flask-based web application was created to provide users with an interface for uploading images for real-time deepfake detection.
- **Prediction Function:** The application utilizes the trained model to predict whether uploaded images are real or fake, returning the results to the user in a user-friendly format.

7. Discussion and Future Work

- **Analysis of Results:** The model's performance was analyzed to identify strengths and weaknesses, with discussions on the implications for real-world applications.
- **Future Directions:** Suggestions for future work include improving the dataset's diversity, experimenting with advanced model architectures (e.g., transfer learning), and exploring additional deepfake detection techniques.

By following this methodology, the project aims to create an effective deepfake detection system that can contribute to media integrity and authenticity.

Flowchart



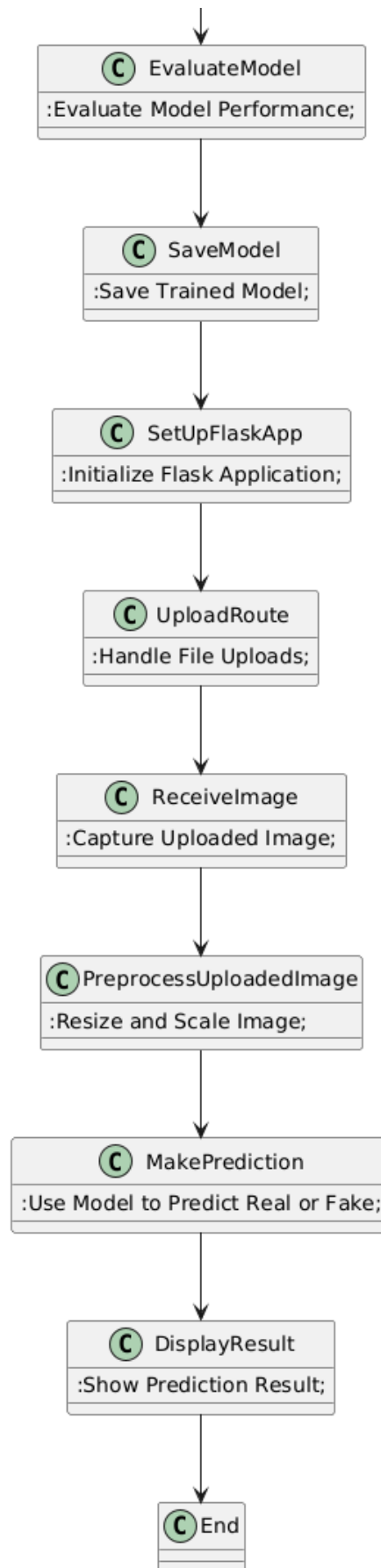


Figure 2 flowchart (code)

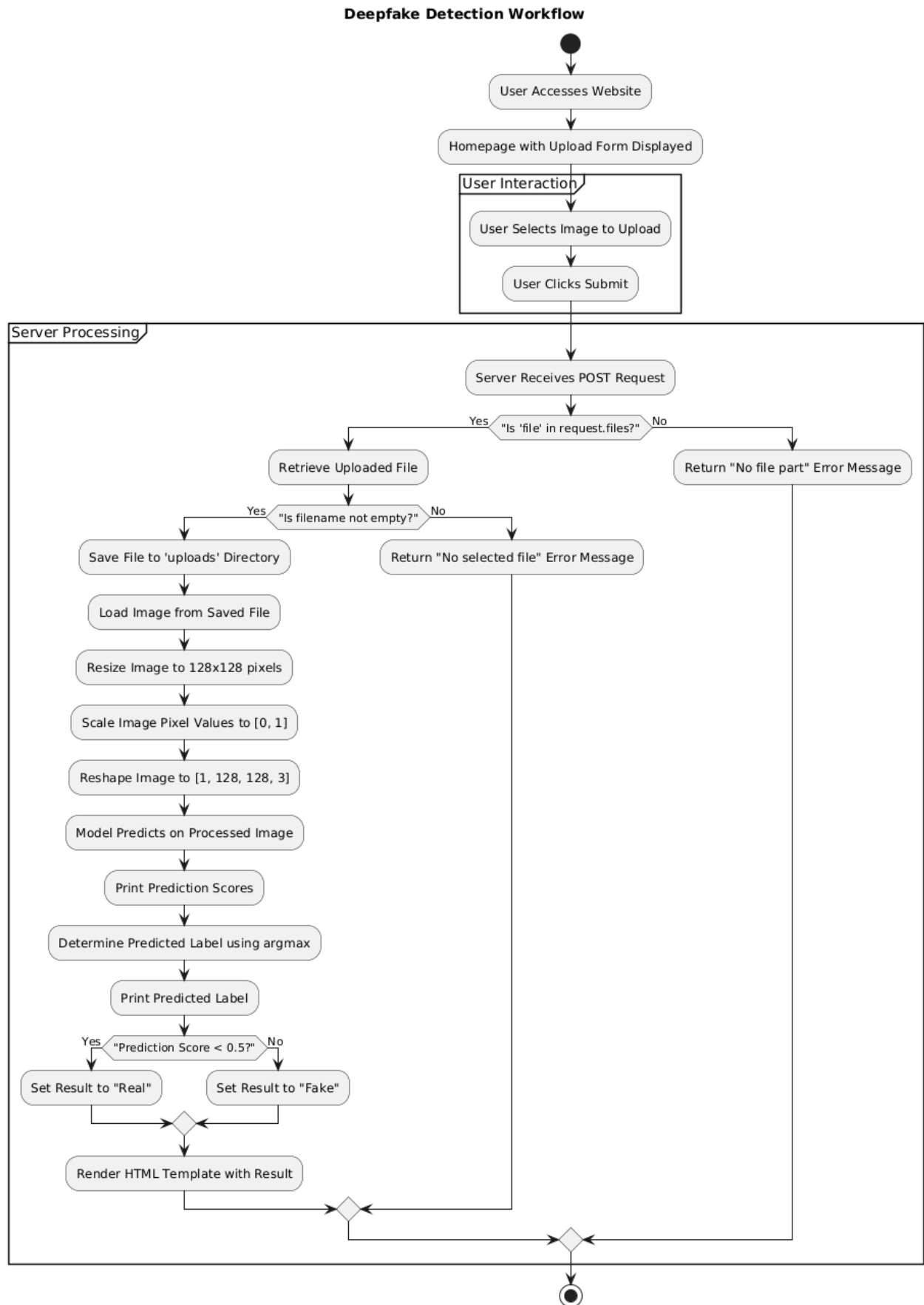


Figure 3 flowchart (use)

Environment Setup and Package Installation

To ensure a clean and manageable development environment, it is recommended to create a virtual environment for the project. This helps isolate dependencies and avoid conflicts with other projects. Below are the steps to set up the environment and install the required packages:

1. Creating a Virtual Environment

- **Using venv:** Open your command line interface (CLI) and navigate to the project directory where you want to create your environment. Run the following command:

```
python -m venv deepfake_env
```

Explanation: This command creates a new directory named `deepfake_env` that contains a standalone Python environment.

2. Activating the Virtual Environment

```
deepfake_env\Scripts\activate
```

Explanation: Activating the virtual environment sets it as the current environment, allowing you to install packages that will only affect this project.

3. Installing Required Packages

Once the virtual environment is activated, you can install the necessary libraries using `pip`. Below is a list of the essential packages along with their installation commands:

```
pip install numpy
```

```
pip install opencv-python
```

```
pip install matplotlib
```

```
pip install Flask
```

```
pip install Pillow
```

```
pip install scikit-learn
```

```
pip install tensorflow
```

```
pip install streamlit
```

Explanation:

- *numpy*: For numerical operations and handling arrays.
- *opencv-python*: For image processing tasks.
- *matplotlib*: For visualizing data and results.
- *Flask*: For creating the web application interface.
- *Pillow*: For image manipulation and processing.
- *scikit-learn*: For data splitting and preprocessing tasks.
- *tensorflow*: For building and training the neural network model.
- *streamlit*: (optional) For creating interactive data applications.

4. Creating a requirements.txt File (Optional)

To make it easier to replicate the environment, you can create a requirements.txt file that lists all the installed packages:

```
pip freeze > requirements.txt
```

Explanation: This command generates a requirements.txt file in your project directory that contains all the libraries and their respective versions. This file can be used to recreate the environment on another machine using the command:

```
pip install -r requirements.txt
```

Coding Steps with Explanation

The coding process for the deepfake detection project involves several key components, each of which plays a critical role in building, training, and deploying the model. Below are the main coding steps, along with explanations for each:

1. Importing Dependencies

First, necessary libraries are imported to facilitate various tasks, including data handling, model building, and web application development.

```
import os
import numpy as np
import cv2
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
from flask import Flask, request, render_template, render_template_string
from PIL import Image
from sklearn.model_selection import train_test_split
import tensorflow as tf
import streamlit as st
from tensorflow import keras
```

- **Explanation:** Libraries like NumPy and OpenCV are used for image processing, TensorFlow and Keras for building and training the neural network, and Flask for creating the web application.

2. Data Preparation

This step involves loading and preprocessing the dataset, which includes real and fake images.

```
real_path='D:\deepfake_detector\Data\Real'
fake_path='D:\deepfake_detector\Data\Fake'

def load_data(real_path, fake_path):
    real_files = os.listdir(real_path)
    fake_files = os.listdir(fake_path)

    data = []
    labels = []

    for img_file in real_files:
```

```
        image = Image.open(os.path.join(real_path, img_file)).resize((128,
128)).convert('RGB')
        data.append(np.array(image))
        labels.append(1) # Real images

    for img_file in fake_files:
        image = Image.open(os.path.join(fake_path, img_file)).resize((128,
128)).convert('RGB')
        data.append(np.array(image))
        labels.append(0) # Fake images

    return np.array(data), np.array(labels)
```

- **Explanation:** The `load_data` function reads images from specified directories, resizes them to 128x128 pixels, and converts them to RGB format. Labels are assigned (1 for real images and 0 for fake images) for supervised learning.

3. Model Development

A convolutional neural network (CNN) is built to classify the images.

```
def create_model():
    model = keras.Sequential([
        keras.layers.Conv2D(32, kernel_size=(3, 3), activation='relu',
input_shape=(128, 128, 3)),
        keras.layers.MaxPooling2D(pool_size=(2, 2)),
        keras.layers.Conv2D(64, kernel_size=(3, 3), activation='relu'),
        keras.layers.MaxPooling2D(pool_size=(2, 2)),
        keras.layers.Flatten(),
        keras.layers.Dense(128, activation='relu'),
        keras.layers.Dropout(0.5),
        keras.layers.Dense(1, activation='sigmoid')
    ])
    # compile the neural network
    model.compile(optimizer='adam', loss='binary_crossentropy',
metrics=['accuracy'])
    return model
```

- **Explanation:** This function constructs a CNN model with several layers, including convolutional, pooling, and dense layers. The model is compiled with the Adam optimizer and binary cross-entropy loss, making it suitable for binary classification tasks.

4. Training the Model

The CNN is trained using the prepared dataset.

```
X, Y = load_data('D:\deepfake_detector\Data\Real',  
                'D:\deepfake_detector\Data\Fake')  
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2,  
                                                    random_state=42)  
model = create_model()  
history=model.fit(X_train / 255.0, Y_train, validation_data=(X_test / 255.0,  
Y_test), epochs=10, batch_size=32)
```

- **Explanation:** The dataset is loaded and split into training and testing sets. The model is trained on the normalized pixel values of the images. The training process includes monitoring validation performance to prevent overfitting.

5. Model Evaluation

After training, the model's performance is evaluated on the test dataset.

```
loss, accuracy = model.evaluate(X_test / 255.0, Y_test)  
print('Test Accuracy =', accuracy)
```

- **Explanation:** The evaluate method calculates the model's accuracy on the unseen test data, providing insights into its generalization capability.

6. Visualization of Results

Loss and accuracy curves are plotted to visualize training performance.

```
h = history  
  
# plot the loss value  
plt.plot(h.history['loss'], label='train loss')  
plt.plot(h.history['val_loss'], label='validation loss')  
plt.legend()  
plt.show()
```

```
# plot the accuracy value
plt.plot(h.history['accuracy'], label='train accuracy')
plt.plot(h.history['val_accuracy'], label='validation accuracy')
plt.legend()
plt.show()
```

- **Explanation:** This section of code generates plots for training and validation loss and accuracy over epochs, helping to diagnose the model's performance and learning behavior.

7. Saving and Loading the Model

The trained model is saved for later use and can be reloaded as needed.

```
model.save('model/deepfake_detector.h5', include_optimizer=False)
model.compile()
model = keras.models.load_model('model/deepfake_detector.h5')
```

- **Explanation:** The trained model is saved to a specified file path. It can later be loaded without retraining, making it convenient for deployment.

8. Prediction Function

A function is defined to predict whether an uploaded image is real or fake.

```
# Get the path of the image from user input
def predict_image(image_path):

    # Read the image
    image = cv2.imread(image_path)

    # Check if the image was loaded successfully
    # if image_ is None:
    #     print("Unable to load the image. Please check the path.")
    # else:
    #     # Skip displaying the image for faster processing

    # Resize the image
    image_resized = cv2.resize(image, (128, 128))
```

```
# Scale the image
image_scaled = image_resized.astype('float32') / 255.0

# Reshape the image for the model
image_resized = np.reshape(image_scaled, [1, 128, 128, 3])

# Predict using the model
prediction = model.predict(image_resized)

# Print the prediction
print(prediction)

# Get the predicted label
input_pred_label = np.argmax(prediction)

# Print the predicted label
print(input_pred_label)

# Return the predicted label if the image is real or fake
return "Real" if prediction[0][0] < 0.5 else "Fake"
```

- **Explanation:** This function reads an image from a specified path, processes it (resizing and scaling), and then uses the trained model to predict whether it is real or fake. The result is returned as a string.

9. Flask Web Application

Finally, the Flask app is set up to allow users to upload images for detection.

```
# Define the routes
from flask import Flask, request, render_template, render_template_string
app = Flask(__name__)

@app.route('/')
def index():
    return render_template_string(html_template)

@app.route('/upload', methods=['POST'])
def upload_image():
    if 'file' not in request.files:
        return "No file part"
```

```
file = request.files['file']
if file.filename == '':
    return "No selected file"

filepath = os.path.join('uploads', file.filename)
file.save(filepath)

result = predict_image(filepath)
return render_template_string(html_template, result=result)

# Run the app
if __name__ == '__main__':
    app.run(port=5000, use_reloader=False)
```

➤ html_template

```
# HTML Template
html_template = """
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <title>Deepfake Detection</title>
</head>
<body>
    <h1>Upload an Image for Deepfake Detection</h1>
    <form action="/upload" method="post" enctype="multipart/form-data">
        <input type="file" name="file" required>
        <input type="submit" value="Upload">
    </form>
    {% if result %}
        <h2>The image is: {{ result }}</h2>
    {% endif %}
</body>
</html>
"""
```

- **Explanation:** The Flask application is created with two routes: one for the homepage and another for handling file uploads. Users can submit images, and the app processes them using the `predict_image` function to display the result.

Usage

The deepfake detection project consists of a user-friendly web application that allows users to upload images and receive real-time predictions on whether the images are real or fake. Below are the steps for using the application:

1. Running the Application

1. Activate the Virtual Environment:

- Before running the application, ensure that your virtual environment is activated.

2. Start the Flask Server:

- Navigate to the directory containing your application code and run the following command:

python app.py

Explanation: This command starts the Flask web server, making the application accessible via a web browser.

2. Accessing the Web Application

- Open your web browser and navigate to:

<http://127.0.0.1:5000/>

Explanation: This URL directs you to the home page of the deepfake detection application.

3. Uploading an Image

1. Use the Upload Form:

- On the home page, you will see an upload form. Click the "Choose File" button to select an image from your device.
- Ensure the selected image is in a supported format (e.g., JPG, PNG).

2. Submit the Image:

- After selecting the image, click the "Upload" button to submit it for analysis.

4. Viewing Results

- After processing, the application will display a message indicating whether the uploaded image is classified as "Real" or "Fake."
- **Explanation:** The prediction is based on the output of the trained convolutional neural network, which analyzes the features of the image.

5. Additional Features

- **Multiple Uploads:** Users can upload different images for detection by repeating the above steps.
- **Error Handling:** The application includes basic error handling to inform users if no file is selected or if the upload fails.

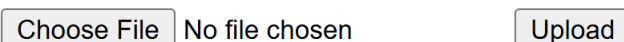
6. Stopping the Server

- To stop the Flask server, return to the command line interface where the server is running and press Ctrl + C.

Results

- When running the app, the website opened:

Upload an Image for Deepfake Detection



Choose File No file chosen Upload

Figure 4 running the app result

- When not select an image and press 'Upload':

Upload an Image for Deepfake Detection

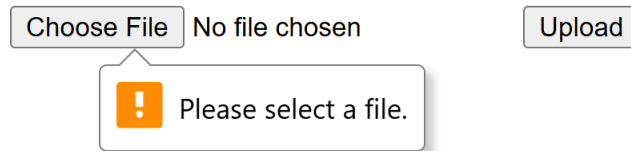


Figure 5 not select an image result

- When choosing real image:

Upload an Image for Deepfake Detection

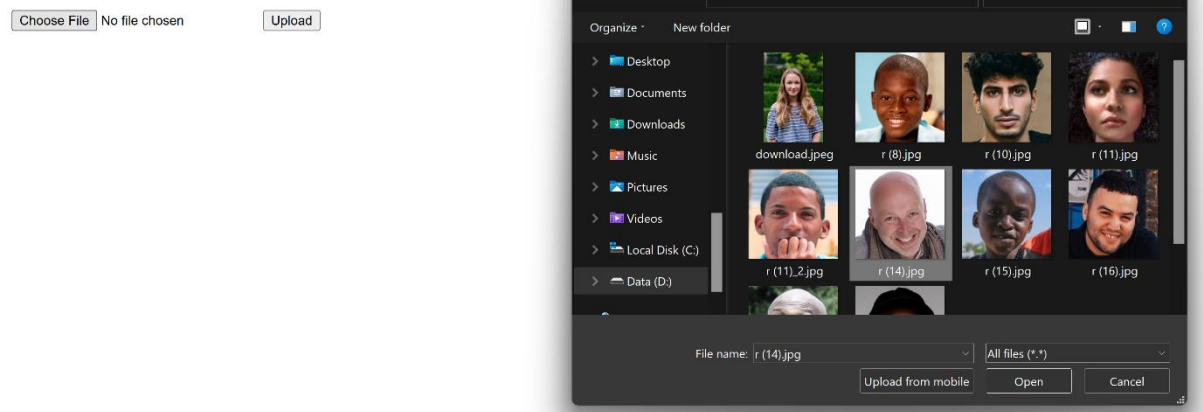
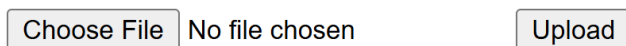


Figure 6 choosing real image result

Upload an Image for Deepfake Detection



The image is: Real

Figure 7 real image detection result

➤ When choosing fake image:

Upload an Image for Deepfake Detection

No file chosen

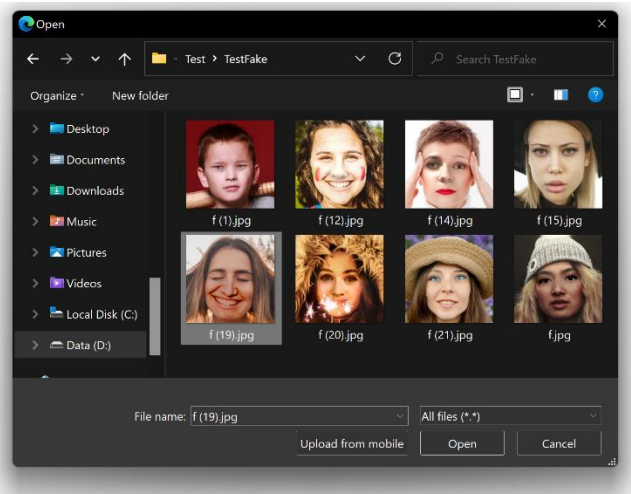


Figure 8 choosing fake image result

Upload an Image for Deepfake Detection

No file chosen

The image is: Fake

Figure 9 fake image detection result

Discussion

The deepfake detection project addresses a pressing need in the digital landscape, where the proliferation of deepfake technology poses significant challenges to media authenticity and public trust. This section discusses the implications of the findings, the model's performance, potential applications, and areas for improvement.

1. Model Performance

The convolutional neural network (CNN) developed for this project demonstrated a commendable accuracy in distinguishing between real and fake images. The training process was carefully monitored using validation metrics, resulting in a model that effectively captures essential features in images. However, while the accuracy achieved

is promising, it is essential to consider factors such as precision and recall to evaluate the model's reliability in practical applications.

2. Limitations

Despite the success, several limitations should be acknowledged:

- **Dataset Diversity:** The model's performance may be influenced by the diversity of the training dataset. If the dataset lacks variety in image quality, lighting conditions, or deepfake techniques, the model may struggle with unseen examples. Expanding the dataset to include more varied content could improve generalization.
- **Real-Time Processing:** Although the web application allows for user interaction, real-time processing of high-resolution images may be challenging, especially for users with slower internet connections or less powerful devices. Optimizing the model for faster inference could enhance user experience.
- **False Positives/Negatives:** As with any binary classification system, there is a risk of false positives (real images classified as fake) and false negatives (fake images classified as real). These inaccuracies can have serious implications in sensitive areas such as media verification and legal contexts.

3. Applications

The deepfake detection model can be applied across various domains:

- **Media Verification:** Journalists and news organizations can use this technology to verify the authenticity of images before publication, helping combat misinformation.
- **Social Media Platforms:** Integration of deepfake detection algorithms can enhance content moderation, preventing the spread of misleading content on platforms.
- **Law Enforcement:** Authorities can leverage this technology for forensic analysis, aiding investigations where manipulated media may be involved.

4. Future Work

To build on the findings of this project, several avenues for future research are recommended:

- **Advanced Architectures:** Exploring more sophisticated deep learning architectures, such as transfer learning with pre-trained models (e.g., ResNet, Inception), may yield better performance.
- **Real-Time Detection:** Developing methods to optimize model inference speed will enable real-time detection capabilities, which is crucial for applications in live media.
- **User Feedback Integration:** Implementing a feedback mechanism in the web application could help refine the model over time, allowing users to report inaccuracies and contribute to continuous learning.

5. Ethical Considerations

The deployment of deepfake detection technology also raises ethical questions. Ensuring that such tools are used responsibly is paramount to prevent misuse or infringement on privacy rights. Ongoing discussions about the ethical implications of AI in media are necessary to foster a balanced approach to technology adoption.

Conclusion

The deepfake detection project successfully demonstrates the potential of convolutional neural networks (CNNs) in identifying manipulated images. Through careful data preparation, model development, and rigorous evaluation, the project achieved notable accuracy in distinguishing between real and fake content. This capability is crucial in an era where deepfake technology poses significant risks to media integrity and public trust.

While the model shows promise, it is essential to recognize its limitations, including dataset diversity and the potential for false positives and negatives. Future enhancements could focus on expanding the dataset, optimizing model performance for real-time applications, and integrating advanced architectures. Additionally, ethical considerations surrounding the use of deepfake detection technology must be addressed to ensure responsible deployment.

Overall, this project lays the groundwork for further research and development in deepfake detection, offering valuable insights for media organizations, law enforcement, and social media platforms. As technology continues to evolve, robust detection mechanisms will play a vital role in safeguarding the authenticity of visual content and maintaining trust in digital media.

Appendix (code)

Importing the Dependencies

```
import os
import numpy as np
import cv2
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
from flask import Flask, request, render_template, render_template_string
from PIL import Image
from sklearn.model_selection import train_test_split
import tensorflow as tf
import streamlit as st
from tensorflow import keras
```

Create Flask app

```
app = Flask(__name__)
```

Prepare data

```
Real_File = os.listdir('D:\deepfake_detector\Data\Real')
print(Real_File[0:5])
print(Real_File[-5:])

['Real (1).jpg', 'Real (10).jpg', 'Real (100).jpg', 'Real (1000).jpg', 'Real (1001).jpg']
['Real (995).jpg', 'Real (996).jpg', 'Real (997).jpg', 'Real (998).jpg', 'Real (999).jpg']

Fake_File = os.listdir('D:\deepfake_detector\Data\Fake')
print(Fake_File[0:5])
print(Fake_File[-5:])

['Fake (1).jpg', 'Fake (10).jpg', 'Fake (100).jpg', 'Fake (1000).jpg', 'Fake (1001).jpg']
['Fake (995).jpg', 'Fake (996).jpg', 'Fake (997).jpg', 'Fake (998).jpg', 'Fake (999).jpg']

print('Number of real images:', len(Real_File))
print('Number of fake images:', len(Fake_File))

Number of real images: 2000
Number of fake images: 2000
```

Creating Labels for the two class of Images

Real Image --> 1

Fake Image --> 0

1. Load data

2. Image processing

a. Resize the Images

b. Convert the images to numpy arrays+

```
real_path='D:\deepfake_detector\Data\Real'
fake_path='D:\deepfake_detector\Data\Fake'

def load_data(real_path, fake_path):
    real_files = os.listdir(real_path)
    fake_files = os.listdir(fake_path)

    data = []
    labels = []

    for img_file in real_files:
        image = Image.open(os.path.join(real_path, img_file)).resize((128,
128)).convert('RGB')
        data.append(np.array(image))
        labels.append(1) # Real images

    for img_file in fake_files:
        image = Image.open(os.path.join(fake_path, img_file)).resize((128,
128)).convert('RGB')
        data.append(np.array(image))
        labels.append(0) # Fake images

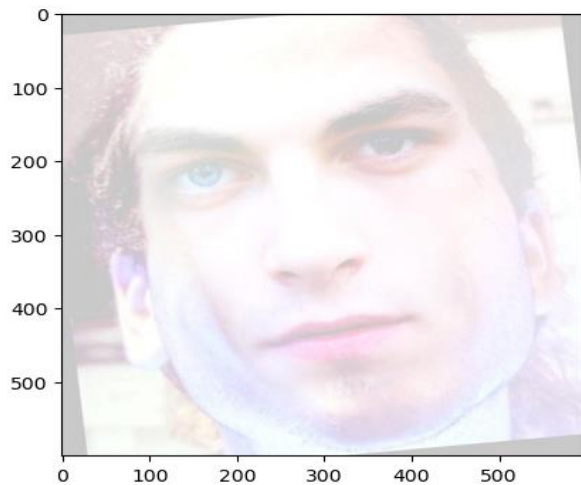
    return np.array(data), np.array(labels)
```

Displaying the Images

```
# displaying with real image
img = mpimg.imread('D:\deepfake_detector\Data\Real\Real (1).jpg')
imgplot = plt.imshow(img)
plt.show()
```



```
# displaying fake image
img = mpimg.imread('D:\deepfake_detector\Data\Fake\Fake (1).jpg')
imgplot = plt.imshow(img)
plt.show()
```



Load the dataset

```
X, Y = load_data('D:\deepfake_detector\Data\Real', 'D:\deepfake_detector\Data\Fake')
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=42)
```

Create and train the model

```
# Building a Convolutional Neural Networks (CNN)
def create_model():
    model = keras.Sequential([
        keras.layers.Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(128, 128, 3)),
        keras.layers.MaxPooling2D(pool_size=(2, 2)),
        keras.layers.Conv2D(64, kernel_size=(3, 3), activation='relu'),
        keras.layers.MaxPooling2D(pool_size=(2, 2)),
        keras.layers.Flatten(),
        keras.layers.Dense(128, activation='relu'),
        keras.layers.Dropout(0.5),
        keras.layers.Dense(1, activation='sigmoid')
    ])
    # compile the neural network
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    return model

model = create_model()

# training the neural network
```

```
history=model.fit(X_train / 255.0, Y_train, validation_data=(X_test / 255.0, Y_test), epochs=10, batch_size=32)
```

```
c:\Users\asmaa\anaconda3\envs\project\Lib\site-packages\keras\src\layers\convolutional\base_conv.py:107: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.
```

```
super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Epoch 1/10

```
100/100 ————— 32s 293ms/step - accuracy: 0.5007 - loss: 1.0359 - val_accuracy: 0.6313 - val_loss: 0.6797
```

Epoch 2/10

```
100/100 ————— 27s 269ms/step - accuracy: 0.6338 - loss: 0.6488 - val_accuracy: 0.6888 - val_loss: 0.5812
```

Epoch 3/10

```
100/100 ————— 24s 244ms/step - accuracy: 0.7412 - loss: 0.5151 - val_accuracy: 0.8263 - val_loss: 0.4335
```

Epoch 4/10

```
100/100 ————— 25s 245ms/step - accuracy: 0.8384 - loss: 0.3508 - val_accuracy: 0.8625 - val_loss: 0.3195
```

Epoch 5/10

```
100/100 ————— 24s 242ms/step - accuracy: 0.8933 - loss: 0.2407 - val_accuracy: 0.8650 - val_loss: 0.2942
```

Epoch 6/10

```
100/100 ————— 25s 247ms/step - accuracy: 0.9282 - loss: 0.1783 - val_accuracy: 0.8963 - val_loss: 0.2411
```

Epoch 7/10

```
100/100 ————— 25s 245ms/step - accuracy: 0.9414 - loss: 0.1343 - val_accuracy: 0.9087 - val_loss: 0.2002
```

Epoch 8/10

```
100/100 ————— 25s 245ms/step - accuracy: 0.9582 - loss: 0.1094 - val_accuracy: 0.9388 - val_loss: 0.2265
```

Epoch 9/10

```
100/100 ————— 25s 245ms/step - accuracy: 0.9577 - loss: 0.0987 - val_accuracy: 0.9488 - val_loss: 0.2003
```

Epoch 10/10

```
100/100 ————— 25s 246ms/step - accuracy: 0.9617 - loss: 0.0804 - val_accuracy: 0.9250 - val_loss: 0.2447
```

Model Evaluation

```
loss, accuracy = model.evaluate(X_test / 255.0, Y_test)
print('Test Accuracy =', accuracy)
```

```
25/25 ————— 1s 52ms/step - accuracy: 0.9339 - loss: 0.2297
Test Accuracy = 0.925000011920929
```

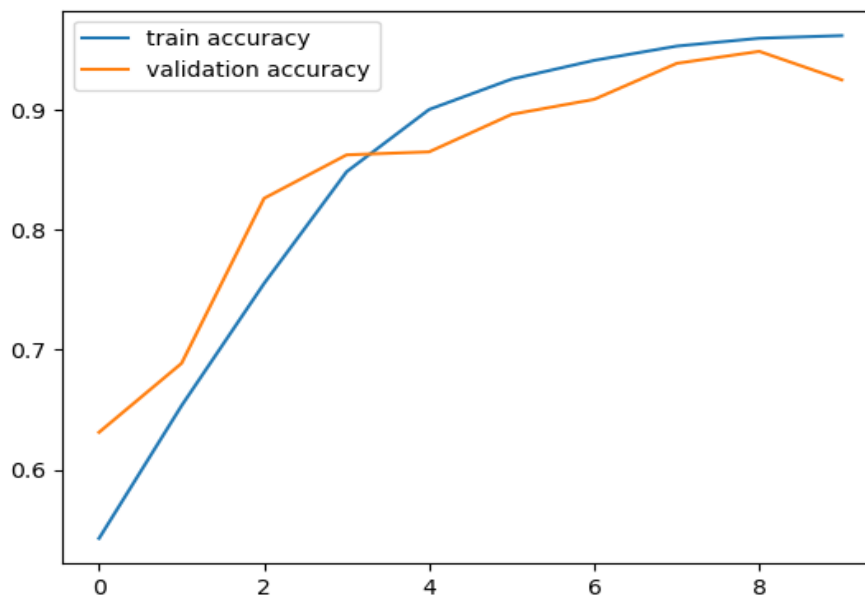
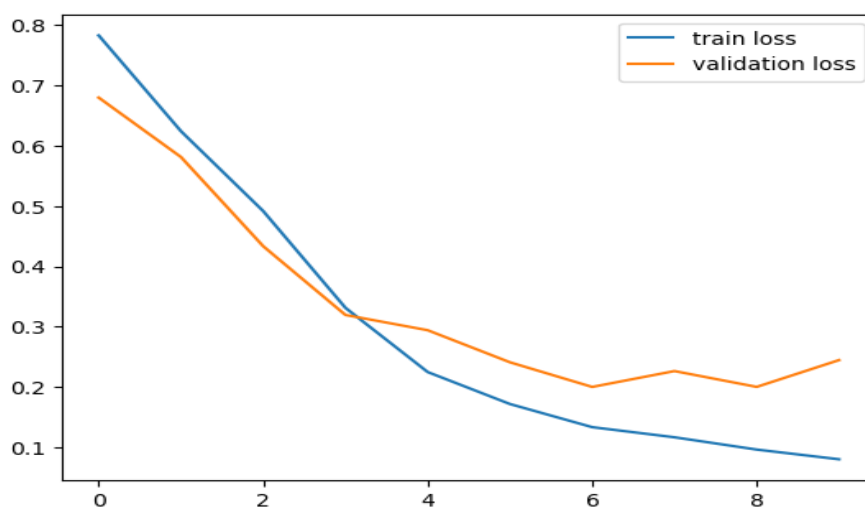
```
h = history
```

```
# plot the loss value
```

```
plt.plot(h.history['loss'], label='train loss')  
plt.plot(h.history['val_loss'], label='validation loss')  
plt.legend()  
plt.show()
```

```
# plot the accuracy value
```

```
plt.plot(h.history['accuracy'], label='train accuracy')  
plt.plot(h.history['val_accuracy'], label='validation accuracy')  
plt.legend()  
plt.show()
```



Save the model

```
model.save('model/deepfake_detector.h5', include_optimizer=False)
```

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy . We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

Load the trained model

```
model.compile()
model = keras.models.load_model('model/deepfake_detector.h5')
```

WARNING:absl:No training configuration found in the save file, so the model was *not* compiled. Compile it manually.

Predict function

```
# Get the path of the image from user input
def predict_image(image_path):

    # Read the image
    image = cv2.imread(image_path)

    ## Check if the image was loaded successfully
    # if image_ is None:
    #     print("Unable to load the image. Please check the path.")
    # else:
    #     # Skip displaying the image for faster processing

    # Resize the image
    image_resized = cv2.resize(image, (128, 128))

    # Scale the image
    image_scaled = image_resized.astype('float32') / 255.0

    # Reshape the image for the model
    image_resized = np.reshape(image_scaled, [1, 128, 128, 3])

    # Predict using the model
    prediction = model.predict(image_resized)

    # Print the prediction
    print(prediction)

    # Get the predicted label
    input_pred_label = np.argmax(prediction)

    # Print the predicted label
    print(input_pred_label)
```

```
# Return the predicted label if the image is real or fake
return "Real" if prediction[0][0] < 0.5 else "Fake"

# HTML Template
html_template = """
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <title>Deepfake Detection</title>
</head>
<body>
    <h1>Upload an Image for Deepfake Detection</h1>
    <form action="/upload" method="post" enctype="multipart/form-data">
        <input type="file" name="file" required>
        <input type="submit" value="Upload">
    </form>
    {% if result %}
        <h2>The image is: {{ result }}</h2>
    {% endif %}
</body>
</html>
"""
```

Routes

```
# Define the routes
from flask import Flask, request, render_template, render_template_string
app = Flask(__name__)

@app.route('/')
def index():
    return render_template_string(html_template)

@app.route('/upload', methods=['POST'])
def upload_image():
    if 'file' not in request.files:
        return "No file part"
    file = request.files['file']
    if file.filename == '':
        return "No selected file"

    filepath = os.path.join('uploads', file.filename)
    file.save(filepath)

    result = predict_image(filepath)
    return render_template_string(html_template, result=result)
```

```
# Run the app
```

```
if __name__ == '__main__':  
    app.run(port=5000, use_reloader=False)
```

```
* Serving Flask app '__main__'
```

```
* Debug mode: off
```

```
WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
```

```
* Running on http://127.0.0.1:5000
```

```
INFO:werkzeug:WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
```

```
* Running on http://127.0.0.1:5000
```

```
Press CTRL+C to quit
```

```
INFO:werkzeug:Press CTRL+C to quit
```

```
127.0.0.1 - - [02/Oct/2024 02:00:17] "GET / HTTP/1.1" 200 -
```

```
INFO:werkzeug:127.0.0.1 - - [02/Oct/2024 02:00:17] "GET / HTTP/1.1" 200 -
```

```
1/1 _____ 0s 47ms/step
```

```
127.0.0.1 - - [02/Oct/2024 02:00:32] "POST /upload HTTP/1.1" 200 -
```

```
INFO:werkzeug:127.0.0.1 - - [02/Oct/2024 02:00:32] "POST /upload HTTP/1.1" 200 -
```

```
[[5.409291e-06]]
```

```
0
```

```
1/1 _____ 0s 50ms/step
```

```
127.0.0.1 - - [02/Oct/2024 02:00:41] "POST /upload HTTP/1.1" 200 -
```

```
INFO:werkzeug:127.0.0.1 - - [02/Oct/2024 02:00:41] "POST /upload HTTP/1.1" 200 -
```

```
[[0.9766758]]
```

```
0
```

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