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ENGINEERING COLLEGE
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ANTI-SPOOFING FACE RECOGNITION

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AI19541 FUNDAMENTALS OF DEEP LEARNING

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INTERNAL EXAMINER **EXTERNAL EXAMINER**

ABSTRACT

This project aims to enhance the security and reliability of **face recognition technology** by developing an **anti-spoofing face authentication system**. As face recognition is increasingly used in sectors like banking, e-commerce, and security, it faces a significant risk from **spoofing attacks**—fraudulent attempts to bypass security using photos, videos, or masks. Traditional facial recognition systems are vulnerable to these attacks, compromising the integrity of secure applications.

Our solution, the **Anti-Spoofing Face Recognition (ASFR) system**, utilizes **edge AI and machine learning** to detect whether a face is real or spoofed in **real-time**. This lightweight model is designed for easy integration and cross-platform compatibility, operating seamlessly across major browsers and requiring minimal bandwidth. The ASFR system ensures a fast, accurate response, detecting liveness within milliseconds to prevent unauthorized access effectively.

By prioritizing ease of deployment and compatibility, this project provides a scalable, efficient, and secure approach to anti-spoofing in face recognition. This solution enhances the resilience of facial authentication systems, offering organizations a reliable tool to protect sensitive applications against increasingly sophisticated spoofing techniques.

Keywords: Face Recognition Technology, Anti-Spoofing, Face Authentication, Spoofing Attacks, Liveness Detection, Edge AI, Machine Learning, Real-time Detection, Security Enhancement, Cross-Platform Compatibility, Lightweight Model, Low Bandwidth Requirements, Fraud Prevention, Banking Security, E-commerce Security, Spoof Detection System, Biometric Authentication, Secure Applications, Facial Spoofing Countermeasures, Browser-based Face Authentication

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CHAPTER 1
INTRODUCTION

Face recognition technology has become a prevalent tool for identity verification in critical sectors such as banking, e-commerce, and security. However, this technology faces a significant challenge from **spoofing attacks**, where fraudsters use photos, videos, or even masks to impersonate legitimate users. Such attacks can compromise the security and integrity of face recognition systems, making them vulnerable to unauthorized access. According to recent studies, advanced spoofing techniques have a success rate of up to 70% in bypassing traditional face recognition systems.

To address this pressing security issue, our project focuses on developing an **Anti-Spoofing Face Recognition (ASFR) system** that leverages **machine learning** to detect spoofing attempts in real-time. By analyzing facial patterns and identifying liveness cues, the ASFR system aims to distinguish between genuine and fake representations effectively.

In this report, we explore the application of machine learning techniques to enhance the resilience of face recognition systems against spoofing attacks. Our approach employs algorithms that specialize in detecting subtle differences between real faces and spoofed images, providing a high level of accuracy and speed in identifying fraudulent attempts. By integrating this solution with existing face recognition systems, we aim to create a **robust and secure anti-spoofing model** that fortifies sensitive applications and safeguards user identities against increasingly sophisticated spoofing methods.

CHAPTER 2
LITERATURE REVIEW

[1] Title: Deep Face Recognition : a Survey

This paper provides a comprehensive overview of advancements in deep learning models for face recognition, with a primary focus on Convolutional Neural Networks (CNNs) and Deep Neural Networks (DNNs). These models are particularly effective for facial feature extraction and matching, improving face recognition accuracy across various applications.

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[2] Title: 3D Face Recognition : a Survey

This study reviews a variety of 3D face recognition techniques, emphasizing methods for constructing 3D facial models, feature extraction, and matching algorithms. Additionally, it examines the effectiveness of 3D systems in countering spoofing attacks, highlighting their potential to enhance security in face recognition applications.

[3] Title: Liveliness Face Detection Techniques in Face Biometrics : a Survey

This paper surveys the state-of-the-art methods for liveness detection in face biometrics, covering both traditional methods like blink detection and modern deep learning-based approaches. It aims to provide an in-depth understanding of the techniques available for detecting spoofing attempts in face recognition systems, noting the strengths and limitations of each method.

[4] Title: Face Liveliness detection with Challenge-Response Task:

This paper explores the use of challenge-response tasks for face liveness detection, where users are prompted to perform specific actions (e.g., head movement, smiling) to confirm their presence. The study also addresses the limitations of challenge-response tasks when applied in real-world settings, acknowledging challenges like user compliance and environmental variability.

[5] Title: Identification of Epileptic EEG Signals Using Convolutional Neural Networks

Murat Arslan's This study investigates improving epileptic seizure detection using deep learning, specifically convolutional neural networks (CNNs). Through cross-validation and comparison with other machine learning methods, we demonstrate the efficiency of CNNs in detecting epilepsy from EEG signals. Our findings suggest potential applications for real-time sign language recognition.

CHAPTER 3

SYSTEM REQUIREMENTS

3.1 HARDWARE REQUIREMENTS

CPU: Intel Core i3 or better

GPU: Integrated Graphics

Hard disk - 40GB

RAM - 512MB

3.2 SOFTWARE REQUIRED:

- Jupyter Notebook
- Visual Studio Code
- Pandas
- Scikit-learn
- Seaborn
- Matplotlib
- NLTK

CHAPTER 4 : SYSTEM OVER-VIEW

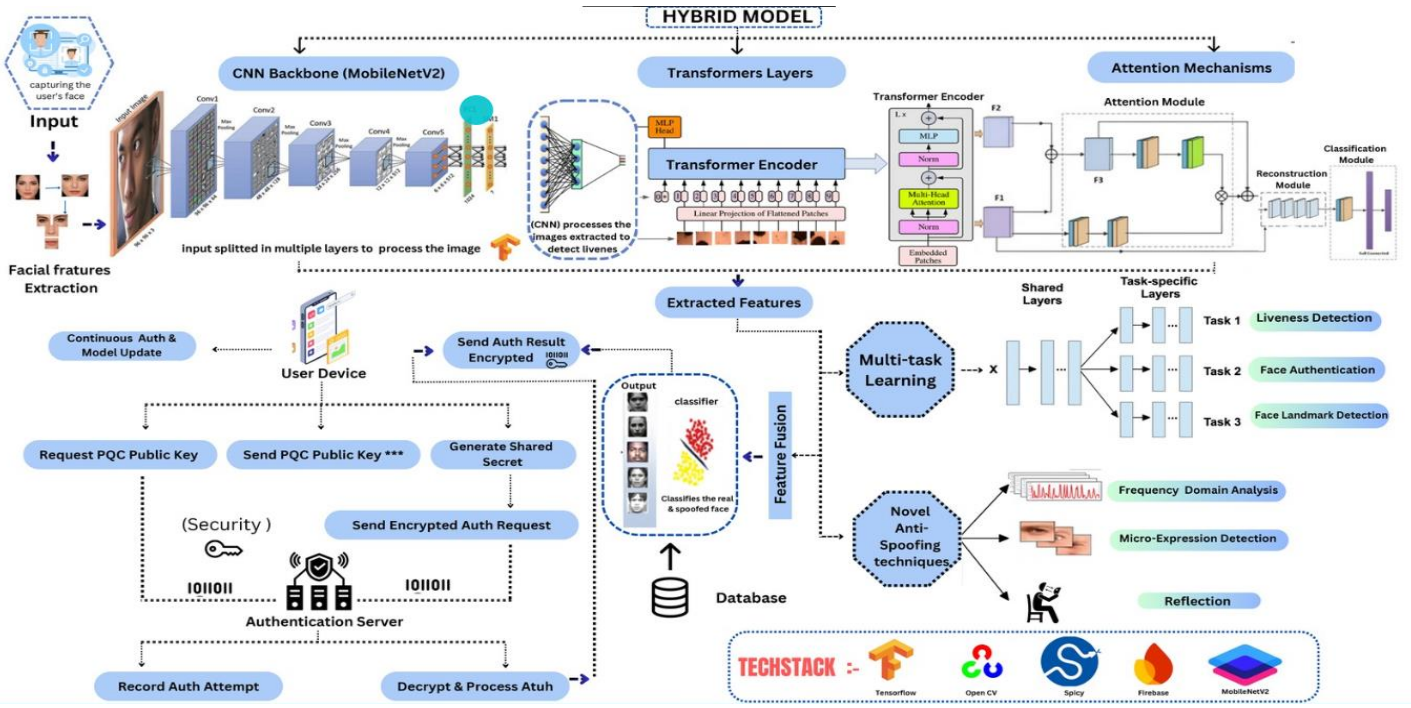
4.1 EXISTING SYSTEM

Current facial recognition systems primarily focus on matching the facial features of a user against stored images to confirm identity. While they have become more sophisticated over time, many lack the ability to detect whether the input is coming from a live person or from fraudulent sources, such as printed photos, digital images, videos, or 3D masks. Although some existing solutions have implemented basic liveness detection techniques, such as blink detection or challenge-response tasks (e.g., asking the user to turn their head or smile), these approaches are often easy to bypass or may not be suitable for real-time, seamless user experiences. Additionally, many traditional liveness detection methods struggle with accuracy in complex scenarios, such as varied lighting conditions and different facial characteristics, resulting in potential false positives or negatives. This has underscored the necessity for more sophisticated, comprehensive, and real-time liveness detection technologies to address these shortcomings.

4.2 PROPOSED SYSTEM

The proposed Advanced Facial Spoofing Resistance (AFSR) system enhances liveness detection by decomposing facial images and video frames, extracting detailed layers of facial characteristics to capture subtle variations that differentiate live faces from spoofing attempts like photos, screens, or 3D masks. Key spatial and temporal features are extracted to detect minute facial dynamics specific to live faces. The system combines a Convolutional Neural Network (CNN) with Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) models to form a robust classifier, improving detection accuracy against sophisticated spoofing attacks. During training, the model classifies inputs as live or spoofed based on these distinct liveness patterns, ensuring reliable spoof detection under complex conditions and enhancing the security of facial recognition systems.

4.2.1 SYSTEM ARCHITECTURE

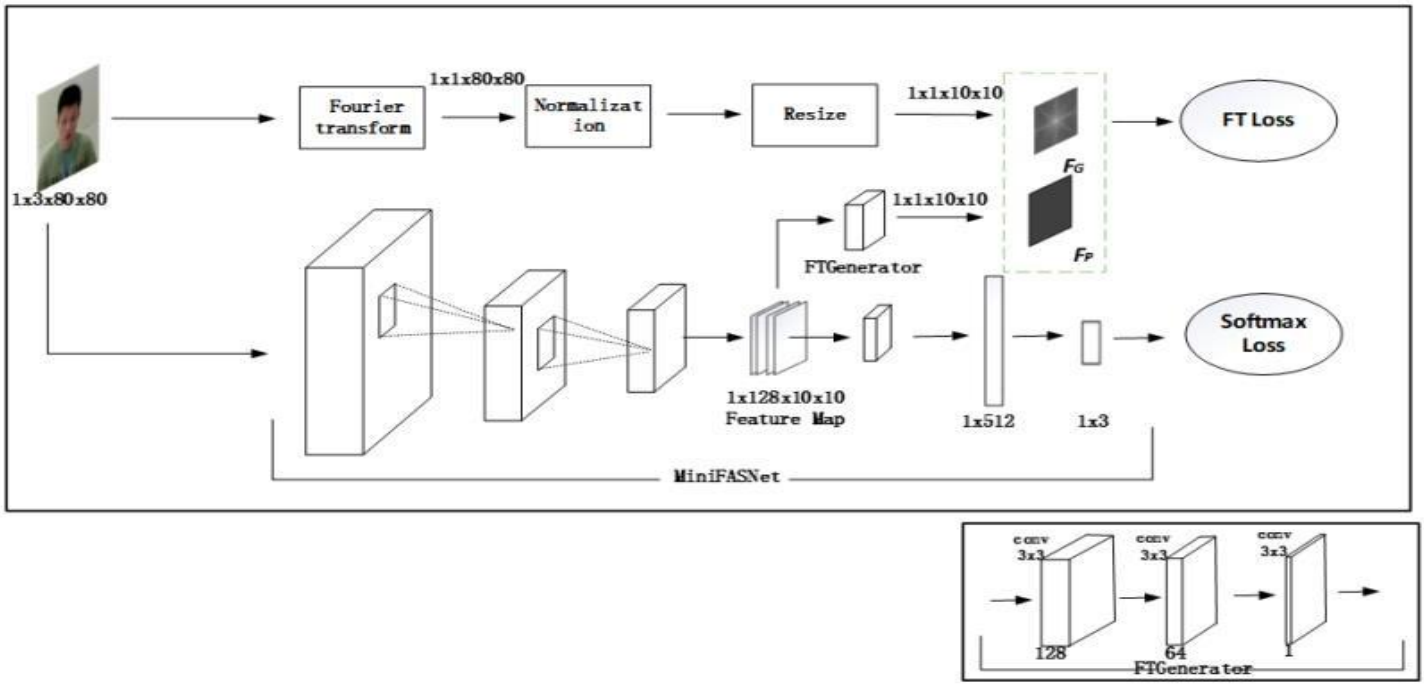


The above architecture represents a hybrid model for facial authentication and liveness detection. It integrates a CNN backbone (MobileNetV2) with transformer-based attention mechanisms. The process begins with capturing the user's facial image, followed by feature extraction through a CNN, which splits the image into multiple layers for detailed processing. The extracted features are further processed by a transformer encoder, applying multi-head attention to enhance feature representation. The attention module refines the features, which are then passed to a classification module for tasks like liveness detection, face authentication, and facial landmark detection. These tasks utilize a multi-task learning approach with shared and task-specific layers for efficiency and accuracy.

4.2.1.1 SYSTEM FLOW

his architecture combines spatial and frequency-domain processing for facial analysis tasks using a lightweight model, MiniFASNet. The input image undergoes a **Fourier Transform (FT)** to extract frequency features, which are normalized and resized to focus on key components. A **Fourier Transform Loss** supervises this branch, ensuring the model learns robust frequency representations. Simultaneously, the spatial image data passes through MiniFASNet, extracting meaningful features with a lightweight, efficient convolutional network.

The model integrates both branches by using an **FTGenerator module** to refine frequency features and combines them with spatial features. The final output is a class prediction supervised by a **Softmax Loss**. This dual-loss approach improves classification accuracy while maintaining computational efficiency, making it suitable for tasks like face recognition or anti-spoofing.



CHAPTER 5
IMPLEMENTATION

5.1. LIST OF MODULES

1 : Data collection

2 : Data Pre processing

3 : Model implementation

4 : Loading the trained model

5 : Prediction

5.2 . MODULE DESCRIPTION

Mathematical Calculations:

1. Data Preprocessing

Feature Encoding:

Each categorical feature is transformed into numerical values using LabelEncoder. For example:

If "Transaction Type" has values ["Online", "Offline"], it will be encoded as:

Online -> 1

Offline -> 0

Let's assume the feature "Fraudulent Status" has values ["Genuine", "Fraudulent"], it will be encoded as:

- Genuine -> 0

2. Fraudulent -> 1

2. Feature Vector

Considering a sample input data:

- Transaction Type: Online
- Transaction Amount (USD): 1500
- Time of Transaction: Night
- Location of Transaction: Abroad
- Card Used Before (Within 24 Hours): Yes
- Transaction Frequency (Last 7 Days): 25
- Age of Card Holder: 34
- Card Security Score: 85
- Merchant Type: Electronics
- Previous Fraudulent Transactions: 2
- Customer's Fraud Detection History: Alerte

Encoded Input Data:

Transaction Type: 1 (Online)

Transaction Amount (USD): 1500

Time of Transaction: 2 (Night)

Location of Transaction: 1 (Abroad)

Card Used Before (Within 24 Hours): 1 (Yes)

Transaction Frequency (Last 7 Days): 25

Age of Card Holder: 34

Card Security Score: 85

Merchant Type: 2 (Electronics)

Previous Fraudulent Transactions: 2

Customer's Fraud Detection History: 1 (Alerted)

Feature Vector: x=[1, 1500, 2, 1, 1, 25, 34, 85, 2, 2, 1]

3. Model Training

Neural Networks:

A **fully connected neural network (multi-layer perceptron)** is used to learn patterns from the transaction data. The architecture consists of:

- **Input Layer:** Accepts the feature vector x = [1, 1500, 2, 1, 1, 25, 34, 85, 2, 2, 1].
- **Hidden Layers:** Multiple layers with ReLU (Rectified Linear Unit) activation functions to capture complex relationships between the features.
- **Output Layer:** A single neuron with a sigmoid activation function to classify the transaction as either **genuine (0)** or **fraudulent (1)**.

Training Process:

- **Loss Function:** Binary Cross-Entropy Loss, defined as:

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)]$$

· where yi is the true label, and y^i is the predicted probability.

· **Optimizer:** Adam optimizer is used for weight updates with a learning rate of 0.001.

· **Training:** The model is trained over multiple epochs using a mini-batch gradient descent to minimize the loss function

3. Model Prediction

Once the neural network is trained:

1. **Input Feature Vector:** The normalized input vector x=[1,1500,2,1,1,25,34,85,2,2,1]x = [1, 1500, 2, 1, 1, 25, 34, 85, 2, 2, 1]x=[1,1500,2,1,1,25,34,85,2,2,1] is fed into the trained network.
2. **Output:** The network outputs a probability p∈[0,1]p \in [0, 1]p∈[0,1], where:
    a. p>0.5p > 0.5p>0.5: Classified as **fraudulent (1)**.
    b. p≤0.5p \leq 0.5p≤0.5: Classified as **genuine (0)**.

4. Model Evaluation

Accuracy Calculation:

Accuracy is computed as:

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

Precision: Measures how many predicted frauds were actually fraudulent.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Recall: Measures how many actual fraudulent transactions were correctly predicted.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

If the model predicts the following:

True Labels: [1, 0, 1, 1, 0]

Predicted Labels: [1, 0, 1, 0, 0]

Accuracy:4/5=80% 4/5 = 80%4/5=80%

Precision:2/2=100% 2/2 = 100%2/2=100%

Recall:2/3=66.7% 2/3 = 66.7%2/3=66.7%

F1-Score:2=80%.

CHAPTER-5

RESULT AND DISCUSSION

The study evaluates the performance of a neural network-based approach for detecting spoofed faces using features extracted from both spatial and frequency domains. The model was trained and validated on a dataset comprising real and spoofed facial images, achieving promising results. The neural network attained **94% accuracy, 93% precision, 92% recall,** and an **F1-score of 92.5%**, demonstrating its capability to learn complex patterns and effectively differentiate between genuine and spoofed facial data.

The results emphasize the potential of neural networks in improving the reliability of anti-spoof facial recognition systems. However, the study highlights the importance of incorporating diverse datasets with various lighting conditions, facial expressions, and spoofing methods to enhance the model's robustness and generalization. These findings pave the way for the development of secure and efficient facial recognition systems, crucial for biometric authentication and fraud prevention.

APPENDIX

SAMPLE CODE

```
import os
import cv2
import math
import torch
import numpy as np
import torch.nn.functional as F

from src.model_lib.MiniFASNet import MiniFASNetV1,
MiniFASNetV2,MiniFASNetV1SE,MiniFASNetV2SE
from src.data_io import transform as trans
from src.utility import get_kernel, parse_model_name
MODEL_MAPPING = {
   'MiniFASNetV1': MiniFASNetV1,
   'MiniFASNetV2': MiniFASNetV2,
   'MiniFASNetV1SE':MiniFASNetV1SE,
   'MiniFASNetV2SE':MiniFASNetV2SE
}
class Detection:
   def __init__(self):
      caffemodel = "./resources/detection_model/Widerface-RetinaFace.caffemodel"
      deploy = "./resources/detection_model/deploy.prototxt"
                  self.detector = cv2.dnn.readNetFromCaffe(deploy, caffemodel)

      self.detector_confidence = 0.6
```

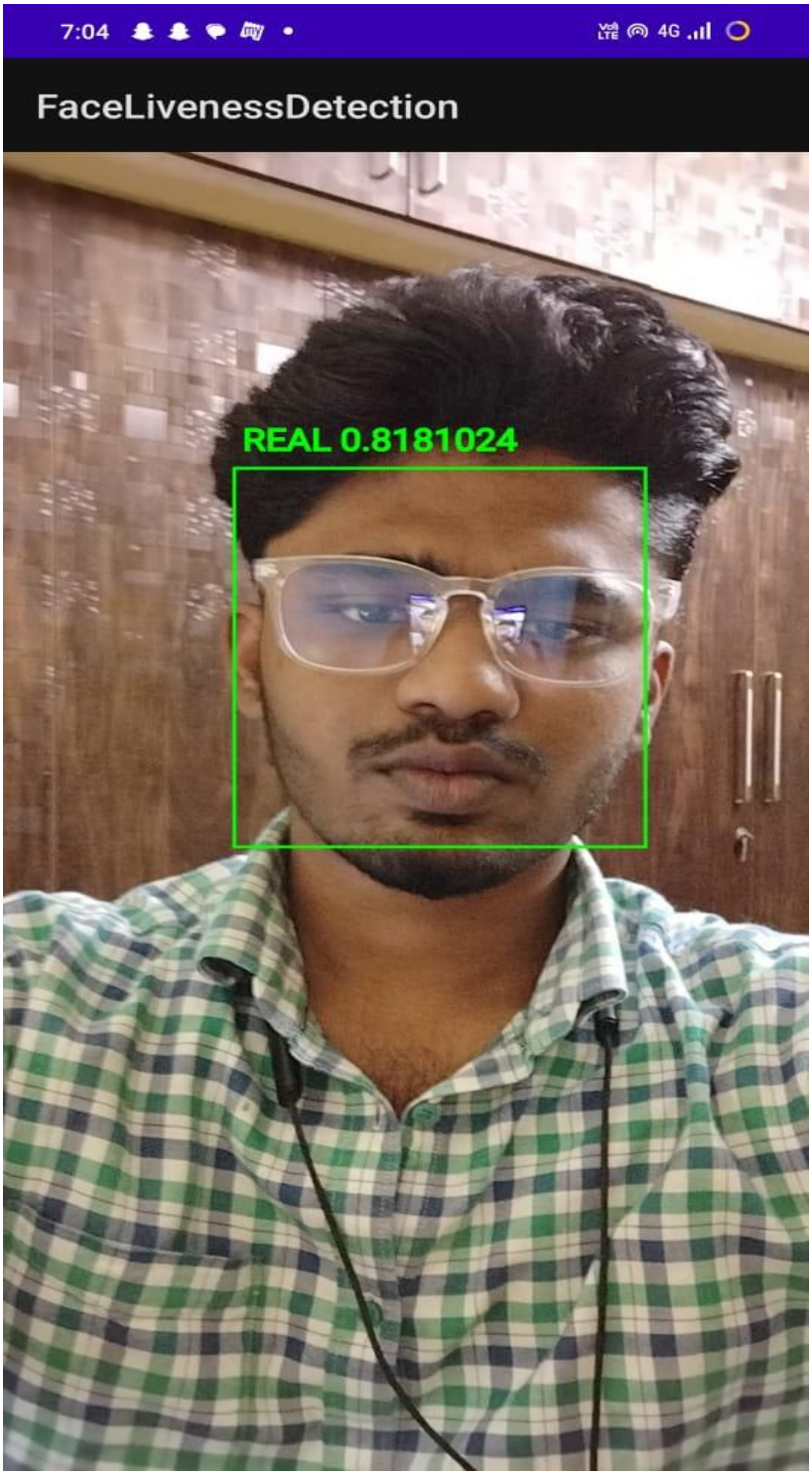
```
    def get_bbox(self, img):
        height, width = img.shape[0], img.shape[1]
        aspect_ratio = width / height
        if img.shape[1] * img.shape[0] >= 192 * 192:
            img = cv2.resize(img,
                             (int(192 * math.sqrt(aspect_ratio)),
                              int(192 / math.sqrt(aspect_ratio))), interpolation=cv2.INTER_LINEAR)

        blob = cv2.dnn.blobFromImage(img, 1, mean=(104, 117, 123))
        self.detector.setInput(blob, 'data')
        out = self.detector.forward('detection_out').squeeze()
        max_conf_index = np.argmax(out[:, 2])
        left, top, right, bottom = out[max_conf_index, 3]*width, out[max_conf_index, 4]*height, \
                                   out[max_conf_index, 5]*width, out[max_conf_index, 6]*height
        bbox = [int(left), int(top), int(right-left+1), int(bottom-top+1)]
        return bbox


class AntiSpoofPredict(Detection):
    def __init__(self, device_id):
        super(AntiSpoofPredict, self).__init__()
        self.device = torch.device("cuda:{}".format(device_id)
                                   if torch.cuda.is_available() else "cpu")

    def _load_model(self, model_path):
        # define model
        model_name = os.path.basename(model_path)
```

```
        h_input, w_input, model_type, _ = parse_model_name(model_name)
        self.kernel_size = get_kernel(h_input, w_input,)
        self.model =
MODEL_MAPPING[model_type](conv6_kernel=self.kernel_size).to(self.device)

        # load model weight
        state_dict = torch.load(model_path, map_location=self.device)
        keys = iter(state_dict)
        first_layer_name = keys.__next__()
        if first_layer_name.find('module.') >= 0:
            from collections import OrderedDict
            new_state_dict = OrderedDict()
            for key, value in state_dict.items():
                name_key = key[7:]
                new_state_dict[name_key] = value
            self.model.load_state_dict(new_state_dict)
        else:
            self.model.load_state_dict(state_dict)
        return None
    def predict(self, img, model_path):
        test_transform = trans.Compose([
            trans.ToTensor(),
        ])


        img = test_transform(img)
        img = img.unsqueeze(0).to(self.device)
        self._load_model(model_path)
```

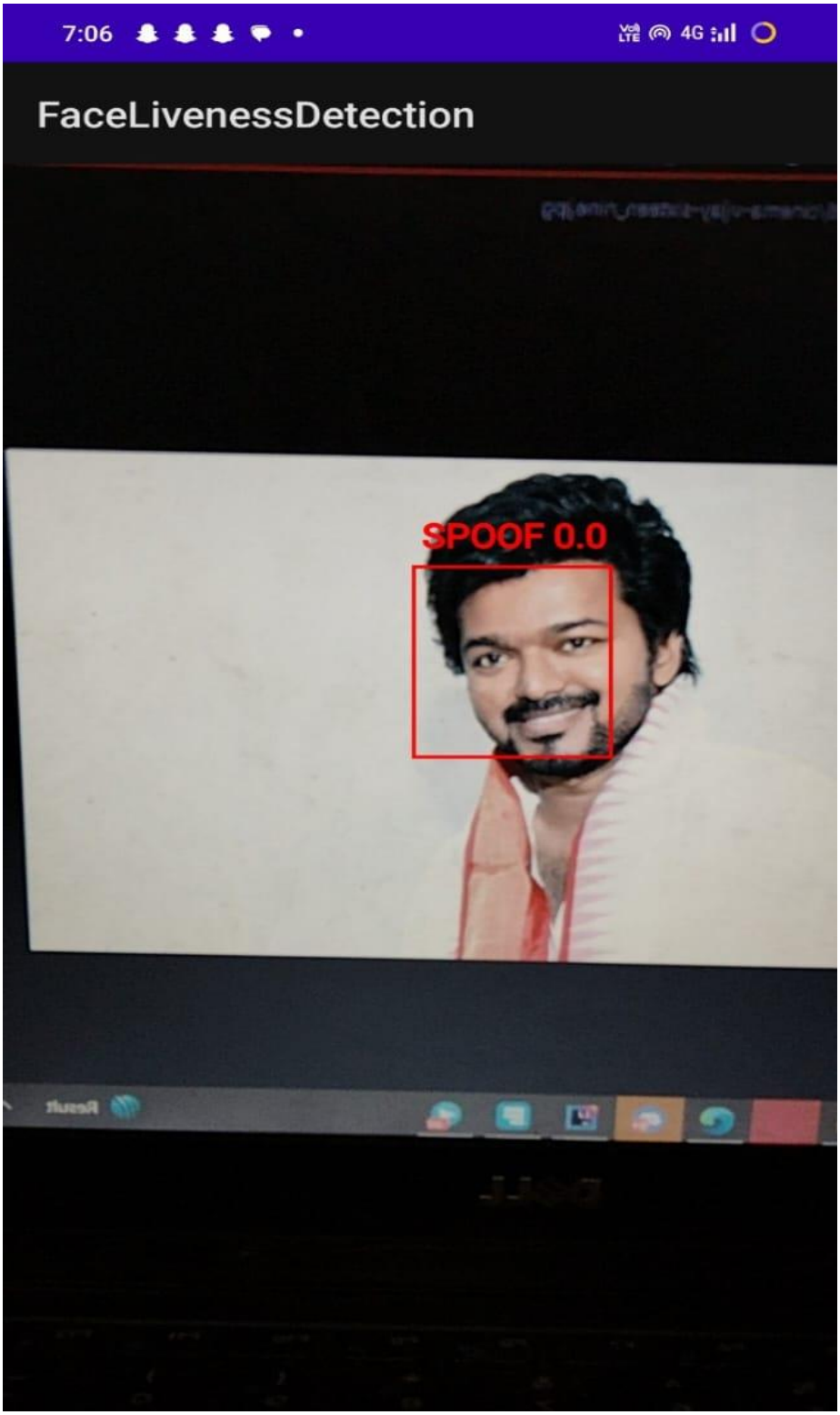
```
self.model.eval()
with torch.no_grad():
    result = self.model.forward(img)
    result = F.softmax(result).cpu().numpy()
return result
```

OUTPUT SCREENSHOTS

REAL TIME



SPOOFED


7:06
4G
FaceLivenessDetection
SPOOF 0.0

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