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Silent Face Anti-Spoofing Liveliness Detection Attendance System

[1]Nichenametla Venkata Sai Priya, [2]Dr.T.Ramashree

[1]M.Tech Student, Department of ECE, S.V. University College of Engineering, Tirupati, Andhra Pradesh, India.

[2] Professor, Department of ECE, S.V. University College of Engineering, Tirupati, Andhra Pradesh, India.

Abstract: This work proposes a silent face attendance system utilizing a Mobile Net Classifier model for liveness detection. The system addresses the challenge of distinguishing real faces from spoofed images (e.g., prints, masks) without requiring user interaction.In this work,we use a combination of Haar Cascade algorithms and MobileNet classifiers to identify live faces. Our system has three modes: registration, login/logout, and spoof detection. During registration, the system only accepts and stores real faces in the database. For existing users, the system records attendance details when it recognizes a genuine face. If a spoof attempt occurs, the system quickly notifies the user with a spoof detection message. By comparing Python-based software between classifiers, we have shown the efficiency and reliability of our method. This integration not only secures the attendance system against spoofing attacks but also records it and provides a smooth and secure user experience, opening doors for future research and advancements in biometric authentication and Local Binary Pattern histogram (LBP) is used for detecting and recognizing human faces in proposed system. It is based on local binary operator, and it is one of the best performing texture descriptors.Suppose consider an image which having dimensions N x M. For every region in an image, we have to divide it into regions of same height and width resulting in m x m dimension.

IndexTerms –Silent face recognition, Anti-spoofing, Liveness detection, Haar Cascaded Classifier, Mobile Net Classifier etc.

1. INTRODUCTION

Biometric attendance systems have become increasingly prevalent due to their convenience and security. However, these systems are not without vulnerabilities, particularly to spoofing attacks where images or masks are used to impersonate authorized users. To address these security issues, anti-spoofing techniques are essential. This work proposes a silent face attendance system using a MobileNet model for liveness detection, providing a robust solution to differentiate real faces from spoofed images (prints, masks) without user interaction.Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have proven highly effective for implementing face recognition systems and resolving their security issues due to their ease of implementation and cost-effectiveness. CNNs, such as Visual Geometry Group networks (VGG-16, VGG-19) and MobileNet, represent advanced architectures that enhance the performance of visual imagery analysis. In addition, transfer learning plays a crucial role in simplifying the implementation of face recognition systems by utilizing pretrained models to expedite the training process and improve accuracy.The proposed system leverages these deep learning advancements to detect and prevent various spoofing attacks, such as print photo attacks and mobile photo attacks. It employs the MobileNet classifier, known for its efficient and fast iterations, making it suitable for real-time applications compared to existing systems. Additionally, the Haar Cascade algorithm simplifies the extraction of facial features through edge and line feature extraction methods. This algorithm classifies positive data points that are part of the detected object (the face) and negative data points that do not contain the object.The proposed system also utilizes the Local Binary Pattern (LBP) histogram for detecting and recognizing human faces. The LBP is based on a local binary operator and is one of the best-performing texture descriptors. It involves dividing an image into regions of the same height and width, resulting in a detailed and accurate representation of facial features.In summary, the proposed silent face attendance system combines advanced deep learning techniques, efficient classifiers, and robust feature extraction methods to achieve high accuracy rates while using fewer datasets than existing methods. This system effectively mitigates vulnerabilities to spoofing attacks, providing a secure and reliable solution for biometric attendance management. The proposed silent face attendance system makes several significant contributions to the field of biometric security and face recognition, building on the advancements outlined in the introduction:

- The system employs the Mobile-Net model for liveness detection, effectively distinguishing between real faces and spoofed images such as prints and masks. This advancement addresses a critical security vulnerability in traditional biometric systems.
- Utilizing the MobileNet classifier, the system achieves faster iterations and real-time processing capabilities, making it more efficient compared to existing systems. This ensures a smooth and responsive user experience.
- The Haar Cascade algorithm simplifies facial feature extraction through edge and line detection, streamlining the processing pipeline and enhancing the system's overall efficiency.
- Implementing the Local Binary Pattern (LBP) histogram for face detection and recognition provides a

highly effective texture descriptor. This method improves the accuracy of recognizing human faces, even with fewer datasets.

- The use of transfer learning facilitates model training by leveraging pretrained models. This approach accelerates the development process and enhances the model's performance, making it easier to implement face recognition systems.
- The system records detailed login and logout information, including date and time, and securely stores images in a database. This ensures comprehensive and reliable attendance tracking and management.
- The proposed system achieves high accuracy rates in liveness detection and face recognition while requiring fewer datasets compared to traditional methods. This efficiency makes the system more practical and scalable.
- By operating silently without requiring user interaction, the system enhances user convenience and experience. This feature is particularly valuable in environments where seamless and non-intrusive operation is critical.

In summary, the proposed work significantly advances the state of biometric attendance systems by providing a secure, efficient, and accurate solution for face recognition and anti-spoofing. Through innovative use of deep learning techniques, efficient classifiers, and robust feature extraction methods, this system addresses key challenges and sets a new standard for biometric security and attendance management.

2. LITERATURE SURVEY

R. B. Hadiprakoso, H. Setiawan, and Girinoto (2020)In their work, Hadiprakoso et al. explored the application of convolutional neural networks (CNN) for face anti-spoofing. They developed a CNN classifier capable of distinguishing between real and spoofed faces with a significant degree of accuracy. Their research demonstrated the potential of deep learning techniques in enhancing the robustness of face recognition systems against spoofing attacks. The use of CNNs allowed for automatic feature extraction and classification, making the system efficient and reliable [1].

Raden Budiarto Hadiprakoso (2020)Hadiprakoso proposed a method that combines eye-blinking detection and HSV (Hue, Saturation, Value) texture analysis for face anti-spoofing. By leveraging the natural and involuntary eye-blinking behavior, along with the textural differences in the HSV color space, the method could effectively identify spoofed faces. This approach highlights the importance of integrating behavioral biometrics and color texture analysis in enhancing face liveness detection.[2]

Gency V, Mrs. Chaithanya C, Mrs. Aysha Fymin Majeed (2020)This survey reviewed various methodologies employed for face spoofing detection, highlighting the strengths and weaknesses of different approaches. The authors categorized the methods into texture-based, motion-based, and hybrid techniques, providing a comprehensive overview of the state-of-the-art in face anti-spoofing. The survey emphasized the need for combining multiple features and methods to improve the accuracy and robustness of spoof detection systems.[3]

Zuheng Ming, Muriel Visani, Muhammad Muzzamil Luqman, Jean-Christophe Burie (2020)Ming et al. conducted an extensive survey on anti-spoofing methods tailored for facial recognition using RGB cameras in consumer devices. The paper highlighted the challenges posed by low-quality images and limited computational resources available in such devices. The survey covered various anti-spoofing techniques, including texture analysis, deep learning, and multi-modal approaches, underscoring the need for efficient and lightweight solutions suitable for consumer electronics.[4]

Hsueh-Yi Sean L (2019)Sean's work focused on the use of convolutional neural networks (CNNs) for face anti-spoofing and liveness detection. The study demonstrated that CNNs could effectively learn discriminative features from facial images, enabling the detection of spoofing attacks with high accuracy. The research also discussed the advantages of CNNs in terms of scalability and adaptability to various spoofing scenarios.[5]

Karuna Grover, Rajesh Mehra (2019)Grover and Mehra proposed an enhanced Local Binary Pattern (LBP) technique for face spoofing detection. The enhanced LBP method improved the traditional LBP by incorporating additional texture descriptors, which made it more robust against various spoofing attacks. The study showed that texture-based approaches could be highly effective in identifying spoofed faces.[6]

Md Rezwan Hasan, S M Hasan Mahmud (2019)Hasan and Mahmud investigated texture-based techniques combined with filtering methods for face anti-spoofing. Their approach utilized various texture descriptors to capture the subtle differences between real and spoofed faces. The filtering methods further enhanced the robustness of the system by reducing noise and improving feature extraction.[7]

Samrity Saini, Kiranpreet Kaur (2019)Saini and Kaur explored the use of K-Nearest Neighbors (KNN) classification for face spoof detection. Their research demonstrated that KNN, a simple yet effective machine learning algorithm, could be used to classify facial images as real or spoofed based on extracted features. The study highlighted the potential of traditional machine learning methods in face anti-spoofing applications.[8]

Shaimaa Mohamed, Amr S. Ghoneim (2019)Mohamed and Ghoneim proposed a method that combines visible and infrared imaging for face spoofing detection. By utilizing texture descriptors in both imaging modalities, the system could capture complementary information that enhanced spoof detection accuracy. This multi-modal approach addressed the limitations of using a single modality and improved the robustness of the anti-spoofing system.[9]

Arida Kartika, Indra Bayu Kusuma et al. (2018)Kartika and Kusuma et al. developed an image spoofing detection system using Local Binary Pattern (LBP) and Local Binary Pattern Variance (LBPV). The combination of LBP and LBPV provided a more detailed analysis of the textural properties of facial images, making the system more effective at identifying spoofed faces. The study demonstrated the importance of advanced texture analysis techniques in face anti-spoofing.[10]

Sakshi Jha, Dr. Neetu Sharma (2018)Jha and Sharma proposed a KNN-based approach for face spoof detection. Their method involved extracting relevant features from facial images and using the KNN algorithm to classify them as real or spoofed. The research showed that KNN could be a viable option for face anti-spoofing, especially when combined with effective feature extraction techniques.[11]

P. Kavitha et al. (2017)Kavitha et al. conducted a comprehensive study on various face spoofing detection systems. The paper reviewed different approaches, including texture-based, motion-based, and hybrid methods, providing insights into their effectiveness and limitations. The study highlighted the ongoing challenges in face anti-spoofing and the need for continuous advancements in this field.[12]

3. PROPOSED METHOD

The proposed method introduces a silent face attendance system leveraging the Mobile Net Classifier model for robust liveness detection. This system addresses the challenge of distinguishing real faces from spoofed images, such as prints and masks, without requiring user interaction, thus providing a seamless and secure user experience.Theprimary stream extractsHaarfeatures from RGB images using Haar Cascaded algorithm, capturing intricate details of the face.Mobilenet classifier in the Convolutional layer, which is crucial for identifying real faces with characteristic real patterns versus fabricated ones by applying Local Binary Pattern Histogram to the resultant output. Both streams further process the extracted features through additional convolutional layers, which are then combined to create a richer representation that incorporates pretrained datsets.Afinal convolutional layer integrates this information to make robust predictions. The training process is guided by separate loss functions for each stream optimizing feature extraction for both domains and enhancing the model's ability to detect spoofed faces. By combining primary and secondary domain analysis within Mobile Net Classifier, this architecture provides a promising approach for secure and reliable silent face recognition, effectively mitigating vulnerabilities to spoofing attacks. The system has demonstrated various outcomes, such as registering a real image, retry prompts for failed attempts, live login and logout detections, and effective responses to spoofing attempts with color photos. Additionally, the system records login and logout details with date and time stamps, and securely stores images in a database, ensuring comprehensive and secure attendance management.

A. BLOCK DIAGRAM

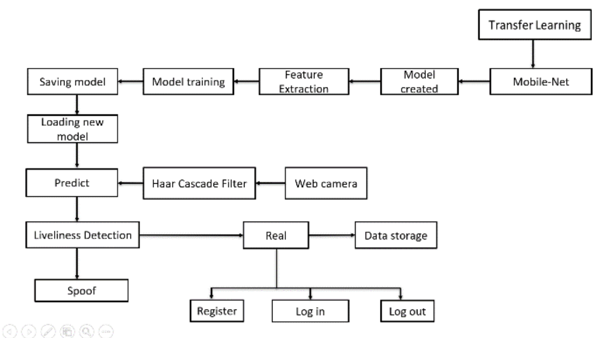


Fig.1: Proposed Block diagram

The proposed method for Silent Face Anti-Spoofing Liveliness Attendance using the Mobile Net Classifierand Haarcascaded classifier.

1.Data Collection:

Image Dataset Compilation: system: The system needs to gather pre-trained sample images. The data is used to train the liveliness detection module. Additionally, real time images can be used which are captured using a webcam.

Data Preprocessing: The images can be resized, cropped, flipped horizontally or vertically and, adjustedfor contrast and brightness.

2.Colour Space Conversion:

- Convert RGB images to grey scale for Statistical Feature extraction.
- Convert RGB images to HSV color space for color feature extraction.

3.Haar Cascade Algorithm:

- Train the Haar Cascade using positive (face) and negative (non-face) images.
- Apply Haar features (edges, lines) to detect faces and eyes within the images

4.Feature Extraction:

- MobileNet, a lightweight CNN model, is employed for feature extraction from the detected faces.
- This involves analyzing the pre-processed images to extract relevant characteristics.
- Local Binary Pattern Histogram (LBPH) is then used to create a feature vector representing the extracted characteristics.
- Calculate luminance, variance, mean of RGB and grayscale values.
- Count data points in grayscale images to differentiate between real and fake images.

5.Classification:

- The MobileNet model, trained on the real face dataset, acts as a classifier.
- It compares the extracted features from the captured image with those in the dataset.
- Based on the comparison, the system classifies the captured image as a real face or a fake one.

5.Model Training:

- The MobileNet model leverages transfer learning to reduce training time.
- It utilizes a pre-trained model as a starting point and fine-tunes it on the dataset of real faces.

Final Identification and Classification: Employ the merged system to identify faces, recognize characteristics, and carry out real-time detection of activity. Offer a conclusive classification as genuine or fake based on the combined criteria.

B.METHODOLOGY

The proposed system methodology for a silent face attendance system leveraging Mobile Net Classifier for liveness detection is designed to effectively distinguish real faces from spoofed images without requiring user interaction. This approach enhances the security and reliability of face recognition systems.

1. Input Image Acquisition: The system begins by capturing an input image of the user's face. This image serves as the foundation for the subsequent liveness detection process.

2. Haar features: The input image undergoes a Haar features to detect the face from the image using Object identification.

3. Mobile Net Classifier Model: The input image is fed into the Mobile Net Classifier model. This model is a lightweight convolution neural network (CNN) specifically designed for efficient liveness detection.Mobile Net Classifier extracts spatial features from the RGB image using its convolution layers. These features capture the intricate details of the face, such as texture and structure, which are critical for differentiating between real and spoofed faces.

4. Local Binary Pattern Histogram (LBPH)

In the computation of the LBP histogram, the histogram has a separate bin for every uniform pattern, and all non-uniform patterns are assigned to a single bin. Using uniform patterns, the length of the feature vector for a single cell reduces from 256 to 59.

5. Feature Integration

- **Combining Features**: The features extracted from the Haar features, MobileNet classifier and Local Binary Pattern Histogram combined to identify real images from spoofed images.
- This integrated representation leverages the strengths of both domains, providing a richer set of features for robust liveness detection.

6. Liveness Detection and Attendance Management

- **Robust Prediction**: The integrated representation is used to make a final prediction on the liveness of the face. The system determines whether the face is real or spoofed based on the combined features.
- **Outcome Responses**: The system demonstrates various outcomes based on the prediction:
    - **Real Image Registration**: Successfully registers real images, ensuring accurate user enrollment.
    - **Retry Prompts**: Prompts users to retry if the system detects a failed attempt, improving user experience and system reliability.
    - **Live Login and Logout Detections**: Accurately detects live login and logout events, preventing unauthorized access and ensuring secure attendance recording.
    - **Spoofing Detection**: Effectively responds to spoofing attempts with color photos, demonstrating robustness against common spoofing techniques.
- **Data Recording and Storage**: Login and logout details, including date and time, are recorded and stored in a secure database. This ensures comprehensive attendance management and traceability.

B. ALGORITHM

1. HAAR-CASCADE ALGORITHM

In this Proposed system, the Haar-Cascade algorithm which is an Object Detection algorithm uses edge or line detection features.Haar-Cascade algorithm classifies positive data points that are part of our detected object and negative data points that don't contain our object.

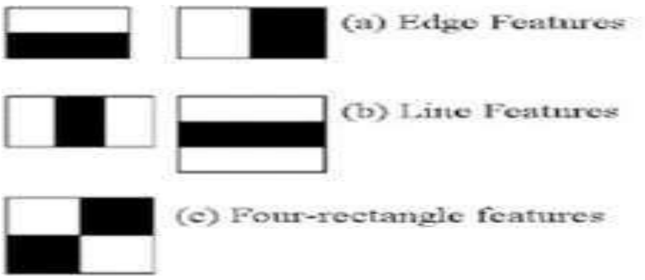


Fig 2: Edge detection and Line detection

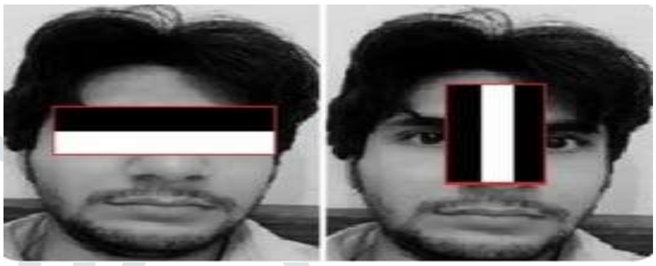


Fig 3: calculating distance between edges of the eyeball to eyeball and forehead to chin

If A<B, then A is lighter than B and B region of face may be an edge of an eyebrow.

If B<A, then B is lighter than A and A region of face may be an edge of an eyebrow. The Value of a single feature can be calculated using, X= Sum of all pixels in the darker region-Sum of all pixels in lighter region Distance between two features can be calculated using,

(Sumofvaluesindarkerregion)/2–(Sumofvaluesinlighter region)/2 ... (1)

Haar Cascade algorithm can be explained in four stages: 1.Calculating Haar Features 2.Creating Integral Images 3.Using Adaboost 4.Implementing Cascading Classifiers .Haar-Cascade detects features by converting the regions in the image of the face area into edges and distance between these edges are calculated. Haar cascades are fast and can work well in real-time.

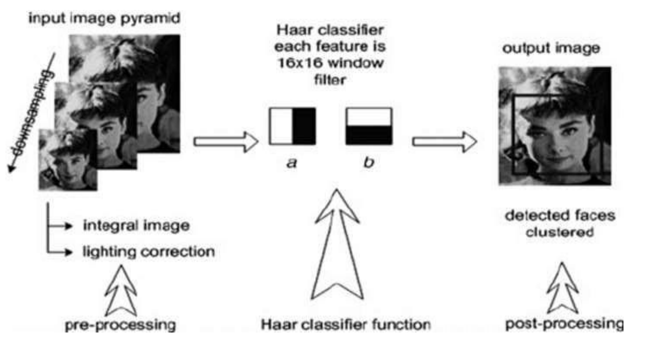


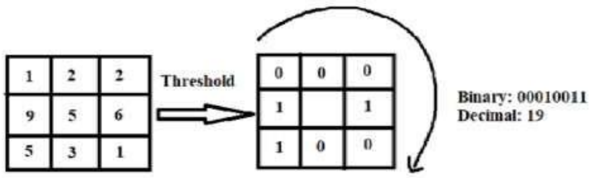
Fig 4: Functionality of Haar - Cascade classifier

2. LOCAL BINARY PATTERN HISTOGRAM (LBPH)

Local Binary Pattern histogram (LBP) is used for detecting and recognizing human faces in proposed system. It is based on local binary operator, and it is one of the best performing texture descriptors.Suppose consider an image which having dimensions N x M. For every region in an image, we have to divide it into regions of same height and width resulting in m x m dimension.

$$LBP(x_c, y_c) = \sum_{p=0}^{P-1} 2^p s(i_p - i_c) \quad \text{.... (2)}$$

'(Xc,Yc)' considered as central pixel with intensity 'Ic'. And 'In' being considered as the intensity of the neighbour pixel. If the value of neighbour is greater than or equal to the central value it is set as 1 otherwise it is set as 0. The obtained decimal number is said to be the pixel LBP value and its range is 0-255



Now we compare the histograms of the test image and the images in the database and then we return the image with the closest histogram.

The Euclidean distance is calculated by comparing the test image features with features stored within the dataset3.Mobile Net Classifier. Mobile-net is a CNN architecture that is much faster as well as a smaller model that makes use of a new kind of convolutional layer, known as Depth-wise Separable convolution along with Point-wise convolution.

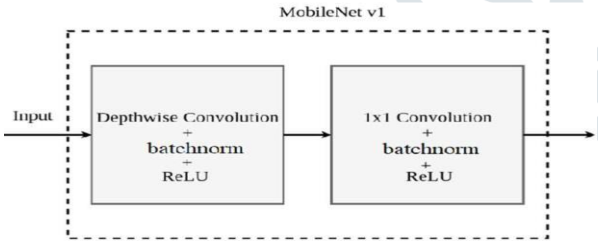


Fig 5: Mobile-Net Architecture

The Mobile-net layers convert the pixels from the input image into output features that describe the contents of the image, and pass these along to the other layers. Hence, Mobile-net is also used as a feature descriptor as well as classifier in proposed system.

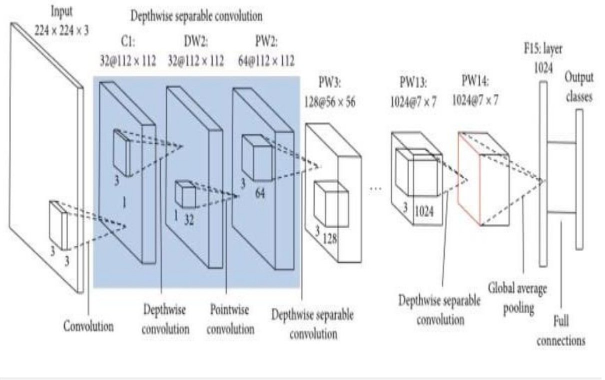


Fig 6: Mobile-net Architecture

3. DEPTH-WISE CONVOLUTION

A depth-wise separable convolution is basically a convolution along only one spatial dimension of the image. Depth-wise convolution with one filter per input channel (input depth) can be written as:

$$\hat{G}_{k,l,m} = \sum_{i,j} \hat{K}_{i,j,m} \cdot F_{k+i-1,l+j-1,m} \quad \text{..(3)}$$

Where, K is the depth-wise convolutional kernel of size DK × DK × M and where the mth filter in ˆK is applied to the mth channel in F to produce the mth channel of the filtered output feature map ˆG.

1. POINT-WISE CONVOLUTION

Pointwise Convolution is a type of convolution that uses a 1x1 kernel.It is a kernel that iterates through every single point.

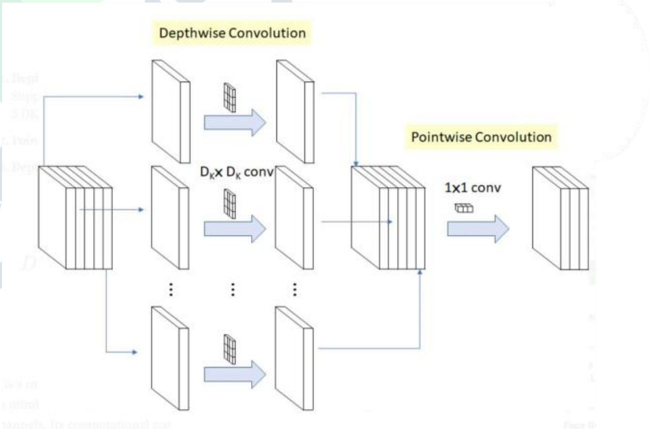


Fig 7: Architecture of Depth-wise Convolution

C. IMPLEMENTATION

1.Start: Initiates the face attendance system process.

2.Capture Input Image: Acquires an image of the user's face.

3.Haarfeatures: Converts the image to the Haar features.

4.MobileNetClassifier: Processes the image to extract spatial features.

5.LBPH: Local Binary Pattern Histogram is used to convert the detected features to Histogram features.

6.Final Convolutional Layer: Integrates combined features for robust prediction.

7.Liveness Detection: Finalizes the liveness detection

8.Decision (Real/Spoofed): Determines if the face is real or spoofed.

- **Register Real Image**: Successfully registers the real image.
- **Retry Prompt**: Prompts user to retry if detection fails.
- **Detect Spoofing**: Identifies and responds to spoofing attempts.

1. **Record Login/Logout Details**: Logs login and logout details with timestamps.
2. **Store Images in Database**: Saves images in a secure database for future reference.
3. **End**: Completes the process.

4. SIMULATION RESULTS

The following explanation provides an overview of the simulation results presented in Figures 8 through 17. Each figure demonstrates a specific aspect of the proposed silent face attendance system utilizing the Mobile Net Classifier andHaar Cascaded classifier model for liveness detection.

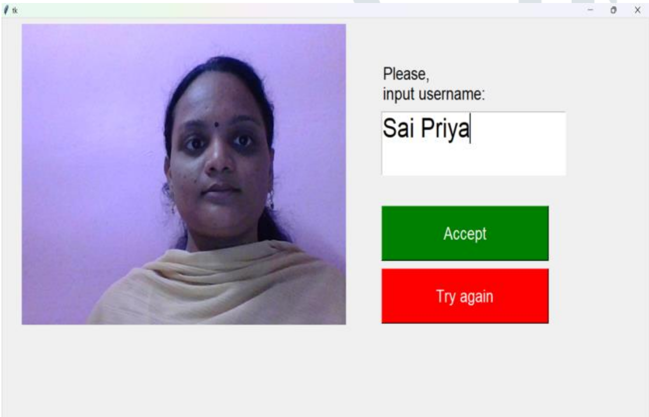


Fig.8:Register a real image

This figure8 shows the systemsuccessfully registering a real image of a user's face. The system captures and processes the real face image, extracting domain features to confirmthe authenticity. Once verified, the image is registered in the system for future recognition.

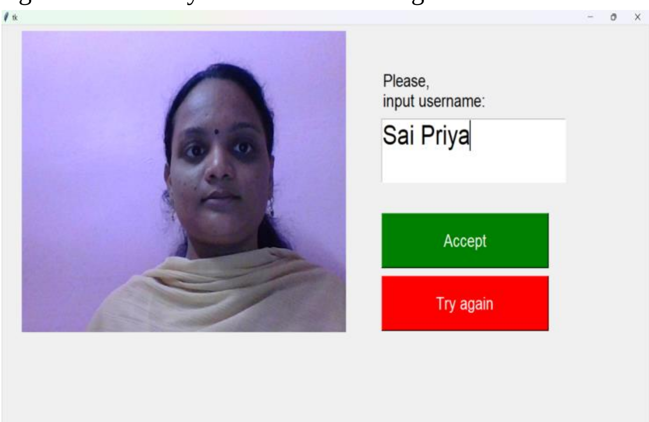


Fig.9:Try again

This figure9 illustrates the system prompting the user to try again if the userwants to retake the face image due to poor quality, occlusion, or any other issue, it prompts the user to retry. This ensures accurate registration and recognition by capturing a clearer image.

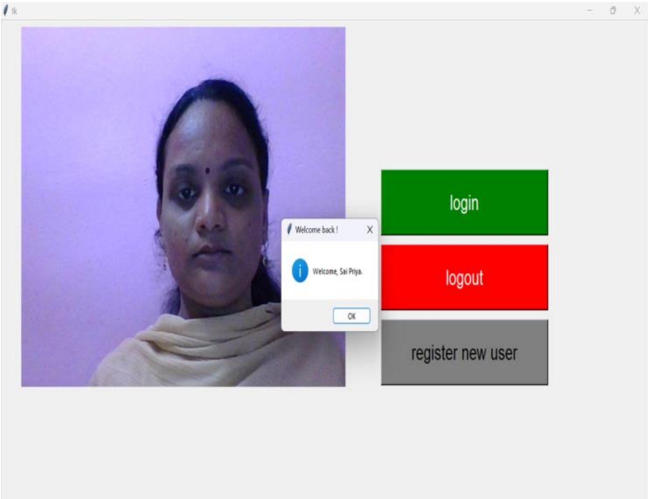


Fig.10: Login in live

This figure 10depicts a successful live login attempt.The system accurately detects the live presence of the user, confirms their identity by matching the live face image with the registered data, and grants access.

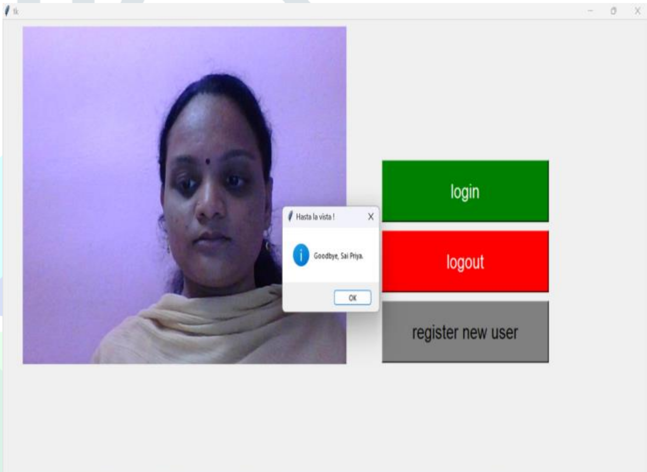


Fig.11: Logout in live

This figure 11shows a successful live logout attempt.The system detects the user's live presence of the user, ensuring that the same registered user is logging out, thereby maintaining the integrity of the attendance records.

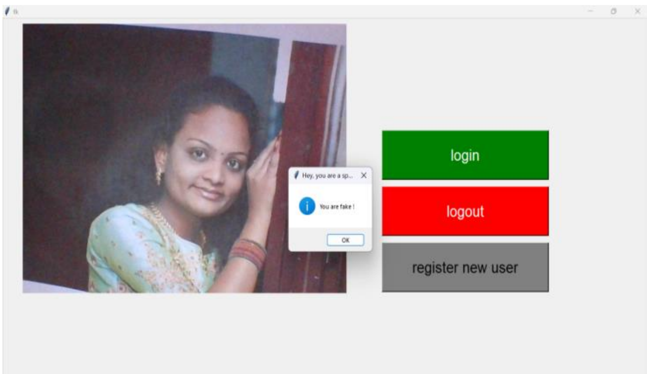


Fig.12: Spoofing with color photo at login

This figure12 demonstrates the system detecting and responding to a spoofing attempt using a color photo at login.The system identifies the lack of live presence and characteristic liveliness patterns typical of a real face. Consequently, it denies access and flags the attempt as spoofing**.**

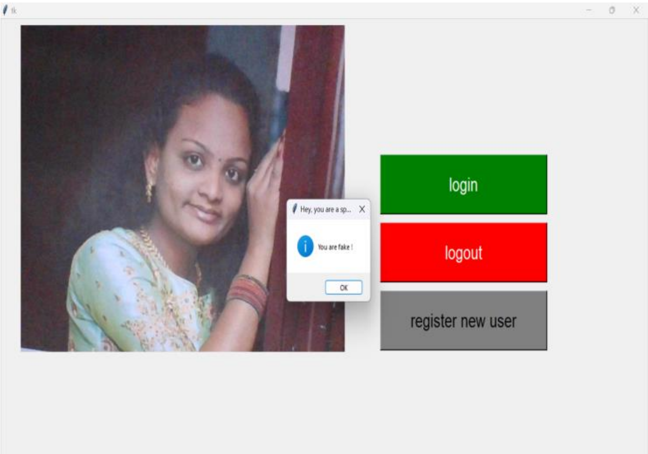


Fig 13: Spoofing with colorphoto at logout

This figure13 shows the system detecting spoofing with a color photo at logout.Similar to the login spoofing detection, the system identifies the fake attempt and denies the logout action, ensuring the security of the attendance records.

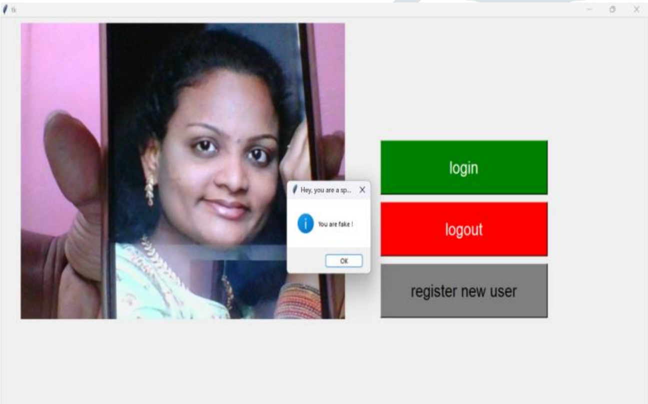


Fig.14: Spoofing with camera at login

This figure 14 illustrates the system detecting a spoofing attempt using a camera (e.g., displaying a video or image on another device) at login.The system detects inconsistencies in the live feed'spatterns and spatial features, thereby identifying and blocking the spoofing attempt.

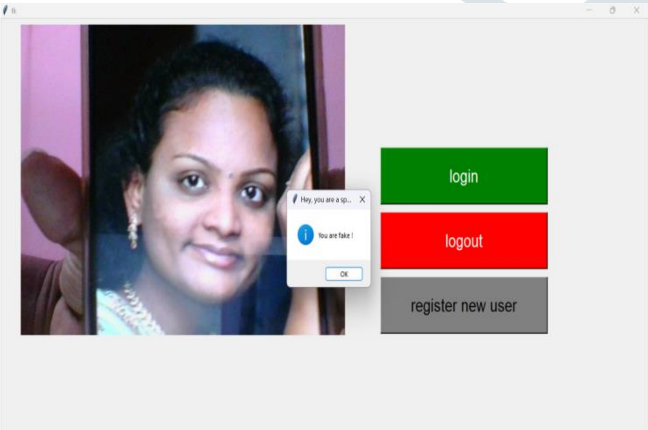


Fig.15: Spoofing with camera at logout

This figure 15depicts the system detecting spoofing with a camera at logout. The system uses similar techniques as in the login spoofing detection to identify the spoofing attempt and deny the logout action, safeguarding the attendance data.

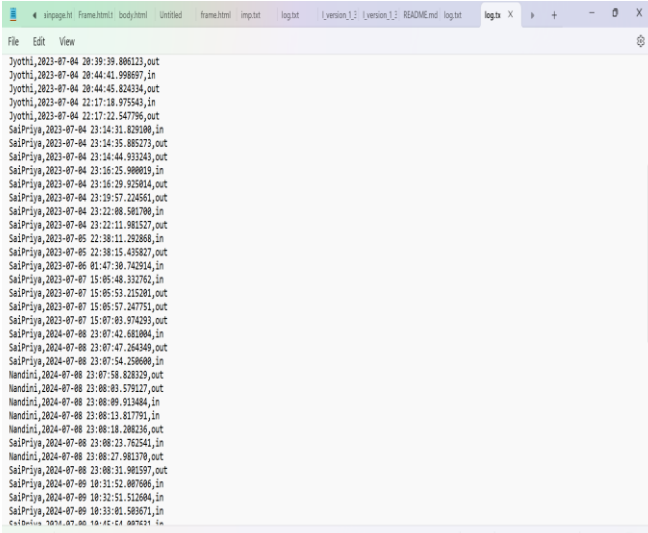


Fig 16: login and logout details with data and time

This figure 16 displays the recorded login and logout details, including date and time.The system logs each login and logout attempt with precise timestamps, ensuring a detailed and accurate record of user activities for attendance management.

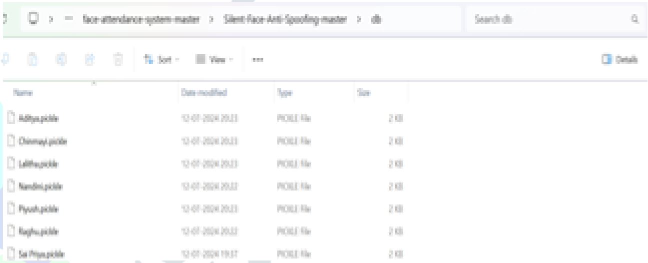


Fig.17: Images stored in database

This figure17 shows the images stored in the system's database.The system securely stores the registered images and captured live images in a database. This allows for future reference, verification, and audit trails, enhancing the overall security and reliability of the attendance system

5. CONCLUSION AND FUTURE SCOPE

The proposed silent face attendance system utilizing the Mobile Net Classifier model for liveness detection effectively addresses the challenge of distinguishing real faces from spoofed images without requiring user interaction. By employing a dual-stream approach that combines spatial feature extraction using convolutional layers by using the Haar features extraction and Local Binary Pattern Histogram, the system achieves robust and accurate liveness detection. The integration of features from both domains enhances the model's ability to detect spoofed faces, ensuring secure and reliable face recognition.The system demonstrated various successful outcomes, including real image registration, retry prompts, live login and logout detections, and responses to spoofing attempts with color photos. Additionally, the system securely records login and logout details with date and time, and stores images in a database, ensuring comprehensive attendance management

FUTURE SCOPE

Further research can be conducted to enhance the system's ability to detect more sophisticated spoofing attempts, such as those using high-quality 3D masks or advanced deepfake technology.

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