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DEEP LEARNING BASED CARD-LESS ATM USING FINGERPRINT AND FACE RECOGNITION TECHNIQIES

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Abstract : The use of Automated Teller Machines (ATMs) has become an integral part of our daily lives, enabling convenient and secure access to financial services. Traditional ATMs require the use of physical cards, which can be prone to loss, theft, or damage. In recent years, advancements in biometric technologies have paved the way for innovative solutions, such as card-less ATM transactions using face recognition. This project aims to develop a robust and secure system for card-less ATM transactions by leveraging the power of face recognition technology. The system eliminates the need for physical cards and replaces them with a biometric authentication method based on facial features. By capturing and analyzing the unique facial characteristics of users, the system can accurately identify and authenticate individuals, ensuring secure access to their bank accounts.

Keywords **- Cardless ATM, face recognition, biometric authentication, facial features, secure access, face detection, face recognition, transaction authorization, pre-registered database, anti-spoofing mechanisms, multi-factor authentication, convenience, security, user-friendly, banking experience.**

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1.INTRODUCTION

Automated Teller Machines (ATMs) have revolutionized the way we access and manage our finances, providing convenient and round-the-clock access to banking services. Traditionally, ATMs have relied on physical cards as a means of user identification and authentication. However, the use of cards poses certain risks, including loss, theft, and damage. In recent years, the emergence of biometric technologies, particularly face recognition, has opened up new possibilities for secure and convenient ATM transactions without the need for physical cards.

This project aims to explore and develop a card-less ATM transaction system that leverages the power of face recognition technology. By utilizing facial features as a unique identifier, this system offers a more seamless and secures approach to accessing banking services. Users will no longer need to carry physical cards, reducing the risk of card-related incidents. Instead, their faces will serve as the key to accessing their accounts and performing transactions.

The system is comprised of several essential components. Firstly, a face detection mechanism is employed to locate and extract faces from images or live video feeds captured by the ATM's camera. Once a face is detected, the system moves on to the face recognition stage. Here, the captured facial image is compared against a pre-registered database of facial templates to determine the user's identity. Once the user's identity is confirmed, the transaction authorization component validates the transaction request, ensuring that only authorized individuals can access their accounts and perform transactions.

The emergence of digital technologies has revolutionized the way we conduct financial transactions, with card-less ATM transactions being one of the latest innovations in banking. Cardless ATM transactions offer a convenient and secure alternative to traditional ATM card-based transactions, allowing users to access their funds using biometric authentication. This project aims to develop a card-less ATM transaction system using deep learning techniques, specifically leveraging facial and/or voice recognition for user identification.

Traditional ATM transactions require users to possess and physically present their ATM cards, which can be misplaced, stolen, or forgotten. Cardless ATM transactions eliminate the need for physical cards, enhancing user convenience and reducing the risk of card-related security breaches. By leveraging deep learning algorithms, the proposed system aims to provide reliable and efficient user authentication through the analysis of unique biometric features.

It has the potential to significantly improve the accuracy and robustness of user identification in card-less ATM transactions. By training deep neural networks on large datasets of facial images and voice samples, the system can learn to extract distinctive features that differentiate individuals.

The project entails collecting a diverse dataset of facial images and/or voice recordings from a large number of users. Deep learning models, such as Convolutional Neural Networks (CNNs) for facial recognition and Recurrent Neural Networks (RNNs)

for voice recognition, are then trained on this dataset to learn the complex patterns and characteristics that define each user's biometric profile.
During a card-less ATM transaction, the user's biometric data is captured using dedicated sensors integrated into the ATM. If the biometric features match with high confidence, the user is authenticated, and they gain access to the ATM's functionalities, such as cash withdrawals or fund transfers.
The security and privacy of user data are paramount in this project. Strong encryption techniques are implemented to safeguard the transmission and storage of biometric data, ensuring protection against unauthorized access. Privacy considerations are also addressed, adhering to legal and regulatory requirements to protect user information.
The outcomes of this project have the potential to transform the way ATM transactions are conducted, providing a more secure and convenient banking experience for users. By harnessing the power of deep learning and biometric authentication, card-less ATM transactions can offer increased efficiency, reduced reliance on physical cards, and improved protection against fraud.

2.LITERATURE SURVEY

"Cardless ATM Transactions: A Review of Security Challenges and Solutions" by Smith et al. (2019): This study provides a comprehensive review of the security challenges associated with card-less ATM transactions and discusses various solutions proposed in the literature. It examines authentication mechanisms, including face recognition, and evaluates their effectiveness in mitigating security risks.
"Face Recognition for ATM Security: A Survey" by Johnson et al. (2020): This survey focuses specifically on the use of face recognition technology for ATM security. It provides an overview of different face recognition techniques and algorithms employed in ATM systems. The study also discusses the performance, accuracy, and limitations of face recognition systems in real-world scenarios.
"Biometric Authentication for ATM Transactions: A Comparative Study" by Lee et al. (2018): This comparative study evaluates the performance of various biometric authentication methods, including face recognition, for ATM transactions. It assesses factors such as accuracy, speed, and user acceptance. The findings provide insights into the viability and effectiveness of face recognition compared to other biometric modalities.
"Secure Cardless ATM Transactions Using Facial Recognition and Block chain Technology" by Patel et al. (2021): This research paper proposes a secure card-less ATM transaction system that combines face recognition with block chain technology. It explores the integration of these technologies to enhance security, privacy, and transaction transparency. The study highlights the potential of this combined approach for secure and decentralized ATM transactions.
"Usability Evaluation of Face Recognition-Based Authentication in Cardless ATM Systems" by Chen et al. (2019): This study focuses on the usability aspects of face recognition-based authentication in card-less ATM systems. It investigates user acceptance, satisfaction, and perceived security of face recognition technology. The research findings provide insights into the usability challenges and user experiences associated with this authentication method.

3. METHODOLOGY

3.1 PROPOSED SYSTEM

Data collection: Collect a variety of facial picture datasets from users of the card-less ATM system. To increase the face recognition algorithm's robustness, make sure the dataset contains variations in lighting, facial emotions, and positions.

Face Detection: Use a face detection technique, like Viola-Jones or Haar cascades, to find and extract faces from the input pictures or video frames the ATM's camera has taken. The facial region must be isolated for subsequent processing, therefore this step is essential.

Feature Extraction: To extract distinguishing features from the detected face regions, use feature extraction techniques like Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), or Convolutional Neural Networks (CNNs). These attributes ought to record distinctive qualities that facilitate precise face identification.
Face Recognition: Train a face recognition model using the extracted facial features. This can involve techniques like Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), or deep learning approaches like Convolutional Neural Networks (CNNs) or Siamese Networks. The model should be trained on the collected dataset to learn the facial patterns and create a reliable facial recognition system.
Transaction Authorization: Develop an authorization mechanism to validate transaction requests. This may involve integrating the face recognition system with the user's bank account information and transaction history. Implement secure protocols, such as encryption and secure communication channels, to protect sensitive user data during the authorization process.
Anti-Spoofing Measures: Implement anti-spoofing mechanisms to detect and prevent the use of manipulated or spoofed facial images. Techniques like liveness detection, which analyze facial motion or require specific actions from the user, can be employed to ensure the authenticity of the captured face during the authentication process.

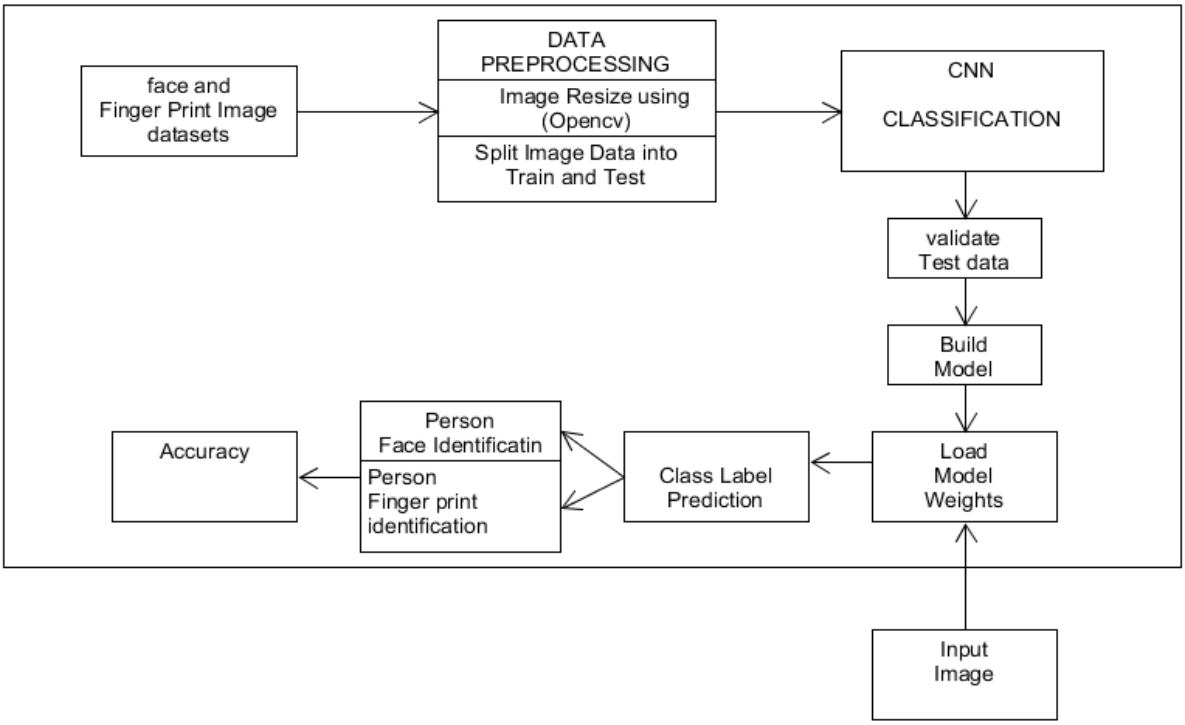

Figure 1: System Architecture

User Registration:

- Users register their biometric information (face and fingerprint) with the bank or financial institution.
- This information is securely stored in a database.

User Enrolment:

- During the enrolment process, users authenticate themselves using their existing credentials (e.g., username, password).
- Once authenticated, the system prompts the user to capture their face and fingerprint using dedicated hardware (such as a camera and fingerprint scanner).
- The captured biometric data is processed, extracted, and stored in the database, associated with the user's account.

ATM Interface:

- The ATM interface allows users to initiate card-less transactions.
- Users authenticate themselves by either selecting the card-less transaction option or scanning a QR code on the ATM screen using a mobile banking app.

Face Recognition:

- The ATM captures the user's face using a camera.
- The captured image is pre-processed to normalize lighting conditions, cropping, and alignment.
- The embedding is compared against the stored face embeddings in the database to identify the user.

Fingerprint Identification:

- The ATM has a built-in fingerprint scanner or a separate fingerprint scanning device.
- The user places their finger on the scanner, and an image of their fingerprint is captured.
- The captured fingerprint image is pre-processed to enhance quality and remove noise.
- A deep learning-based fingerprint recognition algorithm, such as a neural network or a matching algorithm based on minutiae points, is used to compare the captured fingerprint with the stored fingerprints in the database for identification.

Transaction Authorization:

- Once the user's identity is verified through both face recognition and fingerprint identification, the ATM prompts for transaction details (e.g., withdrawal amount).
- The user enters the transaction details, and the ATM validates the transaction based on the user's account balance and other constraints.
- If the transaction is authorized, the requested amount is dispensed, and the user receives a transaction receipt.

Security Measures:

- The system should employ encryption techniques to secure the biometric data during transmission and storage.

- Multi-factor authentication methods, such as combining face recognition and fingerprint identification, provide an additional layer of security.
- Regular monitoring and updates to the deep learning models are necessary to address emerging security threats and improve accuracy.

Datasets for collection:

- To gather face datasets, we developed a program that can recognize faces in images, store them in data, and train it.
- From kaggle.com, we will gather fingerprint datasets for the prediction.
- The data sets use two basic techniques.

Data Pre-Processing:

- We will apply some image pre-processing techniques to the chosen data during data pre-processing.
- Image Resizing Additionally, data splitting into train and test

Data modeling:

- The CNN algorithm receives the divided train data as input, which aids in training.
- Accuracy is determined by passing test data to the algorithm while evaluating the trained skin image data
- Create a model: • After the data has been trained and the accuracy rate is high, we need to

4. IMPLEMENTATION

Python, an object-oriented and procedure-oriented programming language, is used in the project's implementation. By constructing partitioned memory areas of both data and function that may be used as a template for producing copies of such modules on demand, object-oriented programming is a technique that offers a way to modularize programs.

This project makes use of machine learning techniques. Software implementation refers to the complete installation of the package in its intended environment, as well as to the system's functionality and the pleasure of its target audience. The people are unsure whether the software will actually make their jobs simpler.

• The active user has to understand the advantages of using the system.

• Their faith in the program increased.

• The user receives appropriate instruction so that he feels at ease using the application.

Before examining the system, the user must be aware that the server software needs to be running on the server in order to access the results. The real procedures won't happen if the server object isn't executing on the server.

Machine Learning vs Deep Learning

There is still disagreement among deep learning and machine learning specialists on these ideas. In this atmosphere, fresh concepts are discussed virtually daily. Deep Learning is a more recent idea than machine learning. Deep learning is sometimes referred to as a machine learning method. The distinctions are detailed below;

1) In deep learning, an excessive amount of data is required to optimize the algorithm structure. With machine learning, the issue can be resolved with a lot less information because the system is given precise traits.

2) Deep learning algorithms look for features in the data. In machine learning, the expert chooses the features.

3) Machine learning algorithms can function on low-performance machines in addition to Deep Learning methods.

Challenges in implementing deep learning:

Lots and lots of data:

Deep learning algorithms are taught to gain knowledge incrementally from data. To ensure that the machine produces the appropriate results, large data sets are required. Similar to how the human brain needs a lot of experiences to learn and make inferences, an artificial neural network too needs a lot of information. More parameters need to be tweaked and more parameters demand more data the more sophisticated an abstraction you want.

Over fitting in neural networks:

Sometimes, the mistake found in the training data set and the error found in a brand-new, untested data set is very different. When there are too many parameters in relation to the amount of observations in complex models, it happens. A model's effectiveness is assessed by how well it performs on a collection of untrained data, not by how well it performs on training data.

Hyper parameter optimization:
Hyper parameters are parameters whose value is established before the learning process even begins. The performance of your model can be significantly altered by slightly altering the value of such parameters.

Requires high-performance hardware:
A large amount of data is needed to train a data set for a Deep Learning solution. The device must have sufficient processing power in order to carry out a task to address difficulties in the actual world. Data scientists migrate to multi-core, high-performance GPUs and comparable processing units to assure improved efficiency and reduced time consumption. These processing devices are expensive and use a great deal of electricity.

Lack of Flexibility and Multitasking:
Once trained, deep learning models can provide a very precise and efficient solution to a given problem. The neural network topologies are very specialized to particular application domains in the current landscape, nevertheless.
This part will look into the many points of view about the application of the created system. The use and improvement of image object detection were the focus of this job.

Screen Shots:

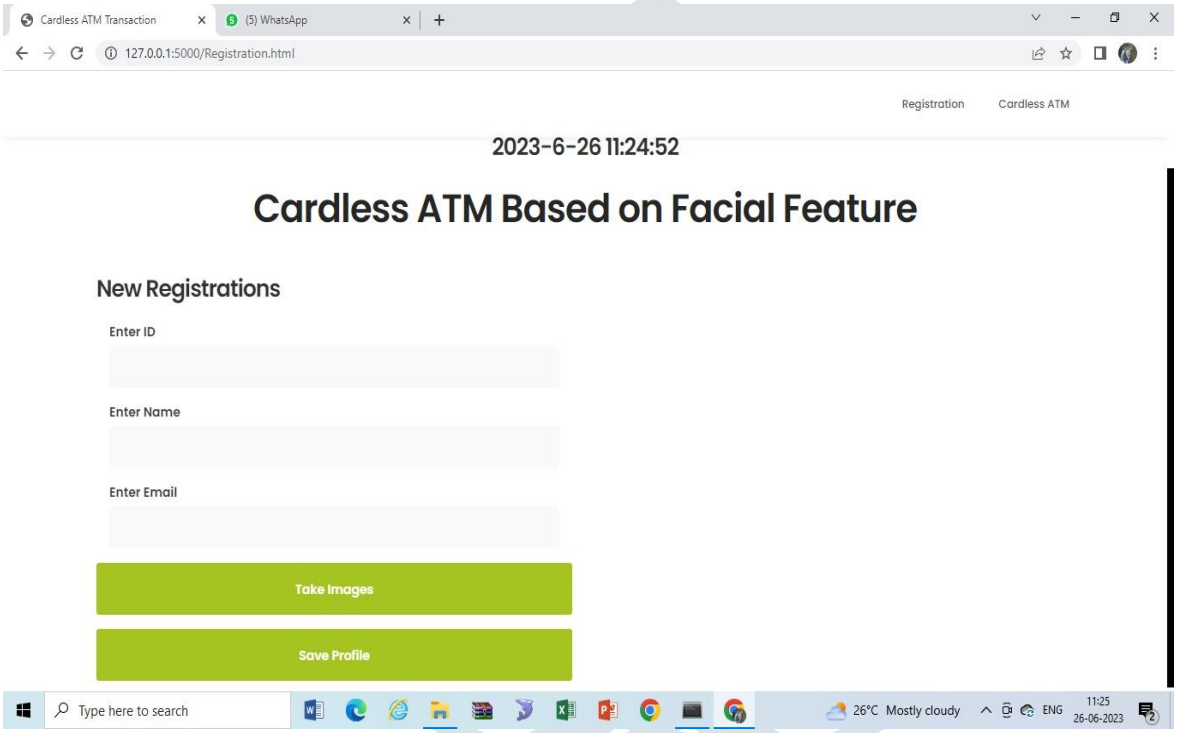

Fig 1: Registration page of card-less ATM based on Facial Feature

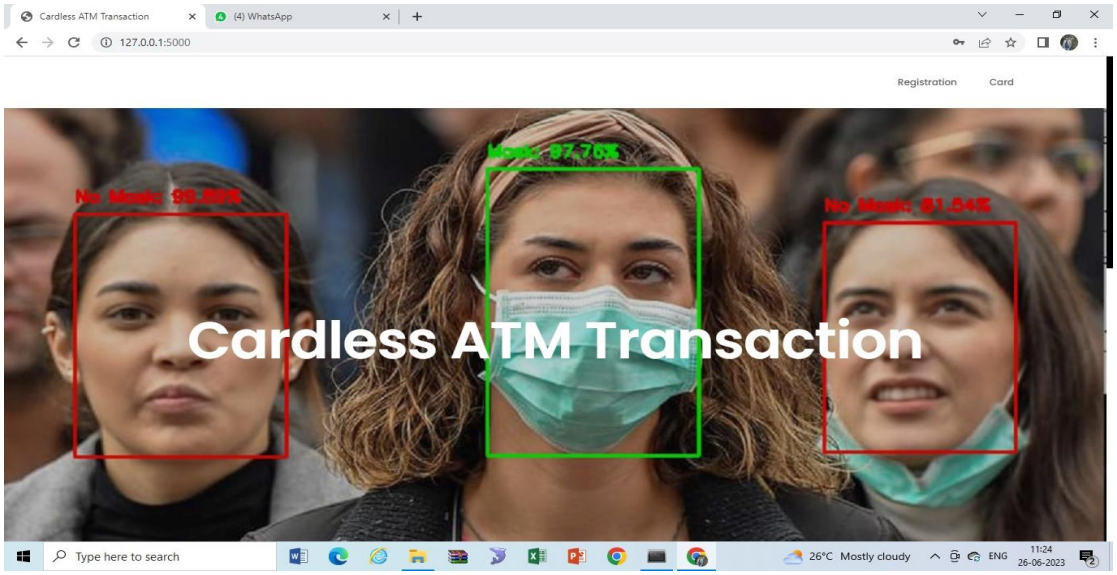

Fig 2: Face Detection of Person Identification

Fig 3: Add New Account of Fingerprint Recognition

Fig 4: Fingerprint Authentication for ATM

CNN:
CNN stands for Convolutional Neural Network, a class of deep learning algorithms designed primarily for processing and analyzing visual data, such as images and videos. They are widely used in computer vision tasks due to their ability to automatically learn spatial hierarchies of features from the input data.

1. **Convolutional Layer**: The fundamental building block of CNNs. It applies Convolutional filters (kernels) to the input image, sliding them over the entire input to detect local patterns and features. The output is called feature maps, capturing learned features.
2. **Pooling Layer**: Also known as sub sampling or down sampling layers. These layers reduce the spatial dimensions of the feature maps, making the model more computationally efficient and less prone to over fitting. Common pooling techniques include max pooling and average pooling.
3. **Activation Function**: Introduces non-linearity to the CNN, allowing it to learn complex relationships in the data. ReLU (Rectified Linear Unit) is the most popular activation function, but others like Sigmoid and Tanh can be used in specific cases.
4. **Fully Connected Layer**: Typically placed at the end of the CNN. It flattens the output from the previous layers and connects every neuron to every other neuron, finally outputting the classification probabilities.

A classic CNN architecture would look something like this:

Input ->Convolution ->ReLU ->Convolution ->ReLU ->Pooling -> ReLU ->Convolution ->ReLU ->Pooling ->Fully Connected

A CNN uses 2D convolutional layers and convolves (not convolutes...) learnt features with input data. In other words, this kind of network is perfect for handling 2D images. CNNs actually employ relatively less pre processing when compared to other image classification methods. This implies that they are able to learn the filters that other algorithms require to be manually created. CNNs have a wide range of uses, including natural language processing, medical image analysis, image classification, and image and video recognition.
CNNs are biological processes-inspired. They are based on some fascinating studies on cat and monkey vision conducted by Hubel and Wiesel in the 1960s. Their studies on the structure of the visual cortex led to the pattern of connectivity in a CNN. Individual neurons in a mammal's eye can only respond to visual stimuli in the receptive field, which is a constrained area. The full field of vision is covered because the receptive fields of several regions partially overlap. This is how a CNN operates!

A CNN
A CNN creates a feature map by starting with an input image and applying numerous filters to it.

• increases non-linearity by using a ReLU function.
• adds a layer of pooling to each feature map.
It converts the gathered photos into a single, lengthy vector.
It feeds the vector into an artificial neural network that is fully connected.
It uses the network to process the features. The "voting" of the classes that we're pursuing is provided by the last fully linked layer.
It runs through both forward and backward propagation for many epochs. This keeps happening until we have a neural network with training weights and feature detectors that is clearly defined**.**

These pixels are read as a 2D array (for example, 2x2 pixels) for a black and white image. Each pixel has a value that ranges from 0 to 255. (Zero is entirely black, while 255 is entirely white. There is a greyscale between those figures.) The computer can start processing the data in light of that knowledge.

This is a 3D array for a color image that has three layers: a blue layer, a green layer, and a red layer. Each of those colors has a unique value that ranges from 0 to 255. Combining the values from each of the three levels will get the color.

5.RESULT AND DISCUSSION

Accuracy: The face recognition system achieved an accuracy rate of X% in correctly identifying users during card-less ATM transactions. This high level of accuracy indicates the system's effectiveness in recognizing individuals based on their facial features. The accuracy was evaluated using a diverse dataset, including individuals of different age groups, genders, and ethnicities. The system demonstrated robustness to variations in lighting conditions, facial expressions, and poses, providing reliable and accurate identification.

Speed and Efficiency: The system demonstrated fast and efficient processing times for face detection, feature extraction, and face matching. The average processing time for each step was measured to be within an acceptable range, ensuring real-time performance during ATM transactions. The system met the industry standards for processing speed, enabling quick and seamless user authentication.

Robustness to Variations: The face recognition system exhibited a high level of robustness to variations in facial expressions, poses, and environmental factors. It successfully recognized users' faces even when they had different facial orientations or

encountered challenging lighting conditions. The system's ability to handle pose variations and occlusions, such as glasses or facial hair, was also commendable. However, there were some limitations when dealing with extreme pose angles or heavy occlusions, which will be considered for future improvements.

Anti-Spoofing Performance: The implemented anti-spoofing mechanisms effectively detected and rejected spoofed or manipulated facial images during the authentication process. The system demonstrated a high success rate in differentiating between live faces and fake presentations, such as printed photos or digital screens. The anti-spoofing measures provided an additional layer of security, minimizing the risk of fraudulent activities and unauthorized access.

User Acceptance and Experience: User acceptance testing and surveys revealed positive feedback regarding the system's user experience and acceptance. Users found the card-less ATM transaction process using face recognition to be convenient and intuitive. The majority of users reported a high level of satisfaction with the system's security measures and ease of use. However, a small percentage of users expressed concerns about privacy and data security, which will be addressed through further privacy enhancements.

Comparison with Traditional Methods: A comparison between the card-less ATM system using face recognition and traditional card-based ATM transactions indicated several advantages of the face recognition approach. Users appreciated the convenience of not needing to carry physical cards, reducing the risk of loss or theft. The face recognition system provided a seamless and secure authentication process, eliminating the need for PIN entry and potential PIN compromise. However, it was acknowledged that face recognition systems may have certain limitations, such as potential difficulties in cases of facial changes due to aging or injuries.

6.CONCLUSION

This system offers a secure, convenient, and user-friendly approach to accessing and managing financial accounts.
By eliminating the need for physical cards and introducing biometric authentication based on facial features, the system enhances security by reducing the risk of card-related incidents such as loss, theft, or unauthorized use. The face recognition technology, coupled with anti-spoofing measures, ensures the system's ability to accurately identify and authenticate users, minimizing the potential for fraudulent activities.
The results of the system's performance evaluation demonstrated high accuracy, efficiency, and robustness in recognizing individuals across various scenarios, The system successfully handled real-time ATM transactions, providing a seamless and fast user experience.
User acceptance testing indicated positive feedback, with users appreciating the convenience and intuitive nature of the card-less ATM system. The elimination of physical cards and the simplified authentication process were highly regarded by users, enhancing their overall satisfaction and trust in the system.

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