

Realtime Secure Clickbait and Biometric Atm User Authentication and Multiple Bank Transaction System

Vijaya G

Professor. CSE Department

*Sri Krishna College of Engineering and Technology
Coimbatore, India vijayag@skcet.ac.in*

Harish U

Student. CSE Department

*Sri Krishna College of Engineering and Technology
Coimbatore, India [19eucs043@skcet.ac.i](mailto:19eucs043@skcet.ac.in)*

Inbavanan R

Student. CSE Department

*Sri Krishna College of Engineering and Technology
Coimbatore, India 19eucs047@skcet.ac.in*

Balachandiran P

Student. CSE Department

*Sri Krishna College of Engineering and Technology
Coimbatore, India 19eucs021@skcet.ac.in*

Amrutha Varshini P

Student. CSE Department

*Sri Krishna College of Engineering and Technology
Coimbatore, India 19eucs011@skcet.ac.in*

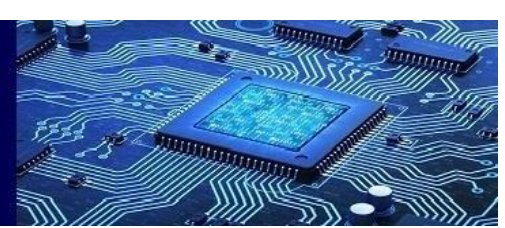
Abstract—The current work focuses on secured ATM transaction of customers using the concept of Deep convolution neural network techniques. The proposed methodology involves series of steps such as face recognition using region proposal network and further processing the image using segmentation techniques to extract facial features for customer identification during money withdrawal. The extracted facial features are segmented with different features for carrying out comparison of captured face image with the facial database. The accuracy, precision, recall and F1 score between the trained model and validation found to be 0.99 which ensures the ability of deep convolutional neural networks in exhibiting superior performance in ATM money transactions.

Index Terms—ATM, DCNN, Neural Network

I. INTRODUCTION

By enabling consumers to conduct self-service operations like cash withdrawals, deposits, and fund transfers without the help of a teller, automated teller machines (ATMs) have transformed the banking sector. Customers also benefit from the convenience of banking services without having to visit an actual bank office thanks to them. While some ATM transactions require a debit or credit card, the majority of them

do not. Luther George Simjian created the first ATM in 1960, and John Shepherd-Barron installed the first one in London in 1967. ATMs can be divided into simple machines that offer basic services like cash withdrawal and balance inquiries, or more sophisticated machines that enable extra services like cash and check deposits, lines of credit, and bill payment. They can also be grouped according to the labels given to them, such as pink label for



women, yellow label for e-commerce, and green label for agricultural use. Nonetheless, ATM fraud is becoming a bigger issue. Criminals prey on unwary users to steal their debit card information and personal identifying details using strategies like skimming, shimming, cash-out, and jackpotting. It's crucial to be on guard and alert for any strange behaviour in order to protect yourself from ATM fraud.

II. LITERATURE SURVEY

According to Seneviratne et al.'s 2020 paper "Impact of Video Surveillance Systems on ATM PIN Security," ATM PINs are a confidential piece of information that is used for transaction authentication. However, in circumstances where the keypad and fingertips are not visible, it is still possible to deduce the PIN using camera footage. In a lab study, the PIN could be deduced by human observers, and the PIN inference

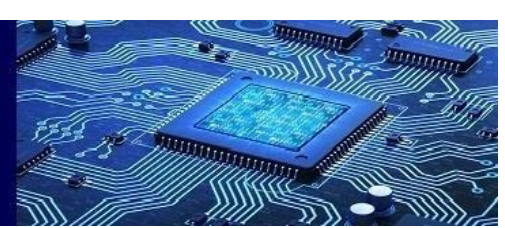
was automated using an OpenCV Python application. The PIN may be disclosed to outsiders by webcam put inside ATM cubicles to increase physical security. This risk can be somewhat reduced by guidelines and regulations for the positioning of security cameras. Yadav et al.'s 2020 paper "Secure Card-less ATM Transactions" proposes a solution to eliminate physical contact between the card and machine during ATM transactions to prevent fraud. The suggested approach entails a mobile app that dynamically creates a one-time security code to produce a unique code for authentication. The user generates a reference number after logging into the mobile app, which is only usable once and is good for a set amount of time. The user then uses the app to enter the user ID, password, and code at the nearby ATM to sign in. The specified amount is withdrawn if the reference number is accurate. This solution offers three levels of protection and gets rid of the issues with OTP sharing. Patil et al.'s 2019 paper "Efficient Cash Withdrawal from ATM Machine Using QRcode Technology" proposes an advanced system to make virtual banking consistent by using QR code technology. The QR code scanner installed in the ATM machine detects and decrypts the information stored in the QR code, including the card number, amount, PIN, CVV number, and other required credentials. After successful authentication with the bank's database, cash is dispensed by the ATM machine.

III. EXISTING SYSTEM

The present ATM authentication procedure uses fixed PINs for identity verification along with access cards that typically feature magnetic stripes and password-PINs. Some systems also use chip and PIN cards as a backup. QR code withdrawal has also been enabled, allowing customers to withdraw cash by scanning a QR code using a mobile app. The proposed system aims to incorporate a new feature into the existing ATM authentication process. ATM security systems can also incorporate biometric authentication using fingerprint recognition, efficient minutiae feature extraction algorithms, and location-based GSM technology for transaction confirmation. However, problems with noisy data, limited degrees of freedom, and spoof assaults plague biometric systems. Gaussian Mixture Models (GMMs), Artificial Neural Networks (ANNs), Fuzzy Expert Systems (FESs), and Support Vector Machines are among the techniques frequently employed for biometric authentication. (SVMs). Using face and speech samples from biometric databases, these algorithms were developed and evaluated. Some of the disadvantages of the current system include lower accuracy, slow face detection and training processes, limited face detection distance, and the need for QR code scanners or mobile apps for some functionalities. Additionally, unimodal biometric systems may face challenges with intraclass variations, non-universality, and unacceptable error rates.

IV. PROPOSED SYSTEM

In this research, a digital facial recognition system using a Deep Convolutional Neural Network is combined with a physical access card to create a multi-modal security model for an ATM. (DCNN). We can recognize faces more accurately using deep learning than we can with conventional machine learning techniques. The multi-modal security model for an ATM proposed in this project combines a physical access card with digital facial recognition utilizing a DCNN. We can recognize faces more accurately using deep learning than we can with conventional machine learning techniques. Filters, kernel size, strides, input shape, kernel initializer, activation, optimizer, batch size and epochs are just a few of the parameters used in the CNN face recognition process. If the taken image and the



saved image conflict, an unidentified face verification link generator will be utilized to create and deliver a Face Verification Link to the user. This will use specialized artificial intelligent agents for remote certification to confirm the identities of illegal users, after which the banking security system will either authorize the transaction as necessary or receive a security-violation alert. The benefits of the suggested system include quick and accurate prediction, reduction of fraudulent attempts, prevention of theft and other criminal activity, provision of a safe and secure lifestyle infrastructure, prevention of unauthorized access using Face Verification Link, and everyone's face ID being unique.

V. METHODOLOGY

The current study proposes a secured method for allowing transactions at ATM and rejects transaction when a criminal or deceiver makes an attempt to withdraw money from ATM. The money dispatch from ATM is done through the verification of the customer after verifying his face. The face recognition of the customer plays a predominant role for issue of money which has been stored earlier in bank's server. The ATM dispatches money only when customer's face gets recognised with the presaved images. The system architecture depicted in figure 1 gives a crystal clear idea about the steps involved in dispatching money to a customer from ATM.

The design includes an ATM simulator, a Next Generation testing tool for XFS-based ATMs. (also known as Advanced Function or Open-Architecture ATMs). A virtualized replica of any ATM can be used for ATM testing thanks to a web-based program called ATM Simulator. ATM Simulator uses virtualization in addition to automated testing for facial authentication and the Unknown facial Forwarder Technique to create a realistic ATM simulation.

A. FACE RECOGNITION

The face recognition phase involves certain steps like face enrollment, face image acquisition and frame extraction. The enrolment of face involves registration of few frontal face of beneficiary templates which can be varied in their position like tilting up and down, zooming closer or far away and turning left or right. For the purpose of image acquisition cameras has been deployed to capture video of the customer entering ATM. The process continues by extracting images from the captured videos through webcam for the purpose of processing further.

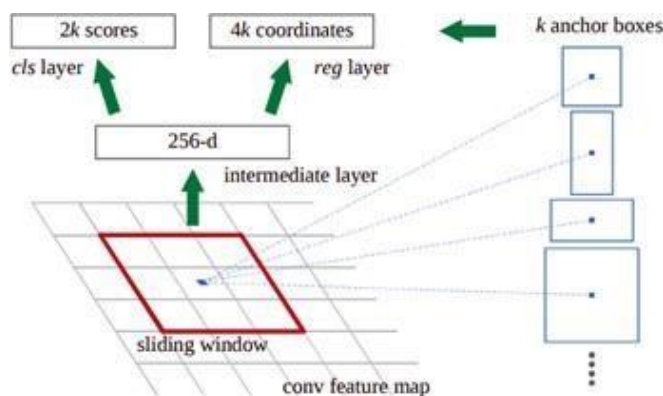
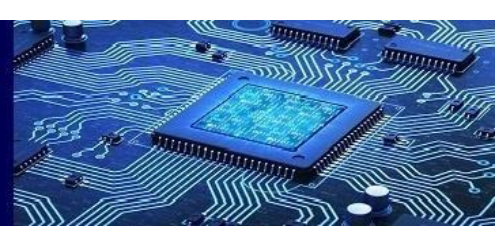


Fig. 1. System Architecture

Normally, 20 to 30 fps are captured and delivered to following stages.

The captured images are further pre-processed to make them suitable for model training and validation. Reading the image, conversion of RGB to grey scale and finally resizing the image to a reduced size from its original size are the steps involved. The process further proceeds with removing the noise from image and subjecting the image for binarization.



B. REGION PROPOSAL NETWORK

An RPN is a fully convolutional network that simultaneously predicts object limits and objectless scores for each location. Each feature (point) on the CNN feature map, on which it operates, is referred to as an Anchor Point. We overlay the image with nine anchor boxes (combinations of various sizes and ratios) for each anchor point. These anchor boxes are centered where the feature map’s anchor point is located in the image. Figure 2 shows the steps involved in Region Proposal Network.

C. TRAINING OF RPN

To be aware that there are nine anchor boxes for each place on the feature map, making a very large total number that does not include all of the essential anchor boxes. An anchor box can be referred to as the foreground if it contains an item or a part of an object, and as the backdrop if it doesn’t.

Therefore, depending on each anchor box’s Intersection over Union (IoU) with the provided ground truth, assign a label to each one for training purposes. We essentially give each anchor box one of the three labels (1, -1, 0). If an anchor has the highest IoU with ground truth, then it is possible

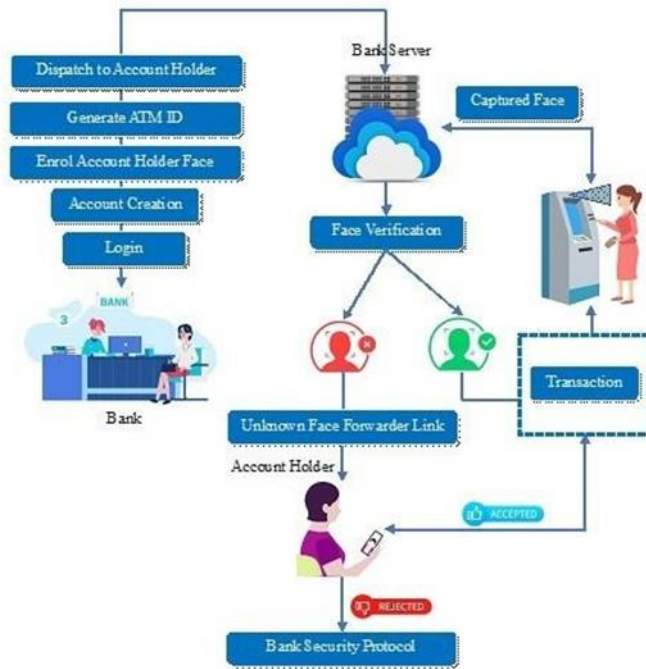
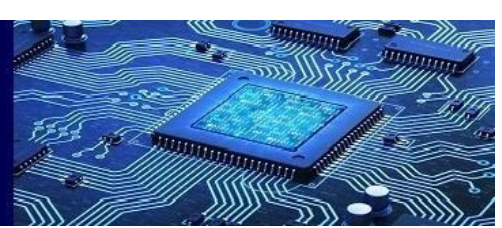


Fig. 2. Region Proposal Network

for such anchor to have label 1. if the ground truth IoU is greater than 0.7. ($IoU_i > 0.7$). If IoU is less than 0.3, an anchor is given the label "-1" (Background). Label = 0: If it doesn’t fit into one of the aforementioned categories, this kind of anchor doesn’t help with training and is disregarded. After labeling the boxes, it generates a mini-batch of 256 anchor boxes that are selected at random from the same image. Backpropagation and stochastic



gradient descent can now be used to train the RPN from beginning to end. (SGD). The steps in processing are choose the first seed point, Add the adjacent pixels' intensity threshold, check the adjacent pixel's threshold, and Selected thresholds for the region's expansion. and the process is repeated until all regions are finished.

D. FACE DETECTION

The Region Proposal Network (RPN) in this module generates RoIs by swiping feature map windows over anchors with different scales and aspect ratios. Face identification and segmentation technique based on enhanced RPN. RoIs are created using RPN, and RoIAlign accurately maintains the precise spatial placements. These are in charge of offering a predetermined collection of bounding boxes of various sizes and ratios that will be utilized as a guide when the RPN initially predicts where items will be placed. Figure 3 shows the steps involved in Face Detection.

E. SEGMENTATION

The current study adopts a straightforward picture segmentation technique called "Region Growing" is based on the region's seeds. It is sometimes referred to as a pixel-based technique because it selects the initial seed spots for picture segmentation. This segmentation method looks at the pixels that are in the immediate vicinity of the original "seed points" and decides whether or not to include the neighbors in the region depending on predefined criteria. In a typical region-growing method, only the "intensity" constraint is used to analyze the neighboring pixels. The intensity value is compared against a threshold, and the neighboring pixels that meet the threshold are chosen to expand the region.

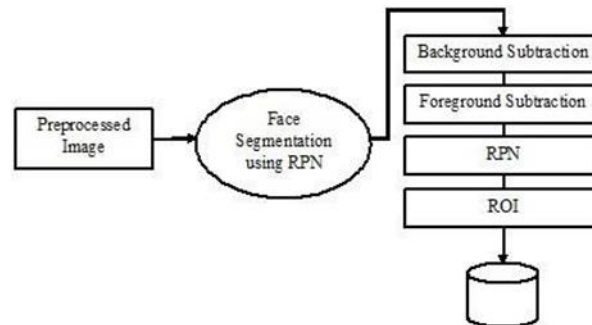
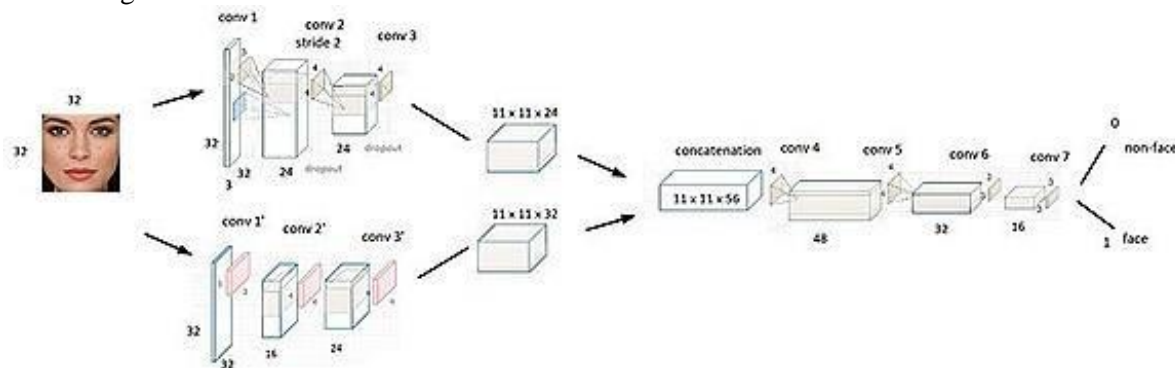




Fig. 3. Steps involved in Face Detection

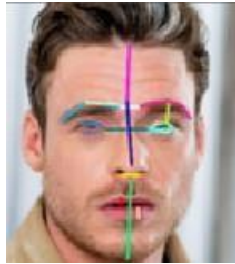


Fig. 4. Image under Feature Extraction

F. FEATURE EXTRACTION

Following face identification, the feature extraction module uses the face image as input to identify the most important aspects for classification. The association between each pose’s facial characteristics and frontal face templates is used to calculate the effects of the change. These features include the eyes, nose, and mouth. Forehead Height , Middle Face Height , Left Eye Area and Nose Length are few examples for facial information. Figure 4 shows the image considered for extraction features from facial images and figure 5 shows the steps involved in Segmented Image Processing

G. FACE CATEGORIZATION

When enrolling, offensive face photos were automatically detected and rejected using DCNN algorithms. This will ensure proper enrollment, which will lead to the best perfor-

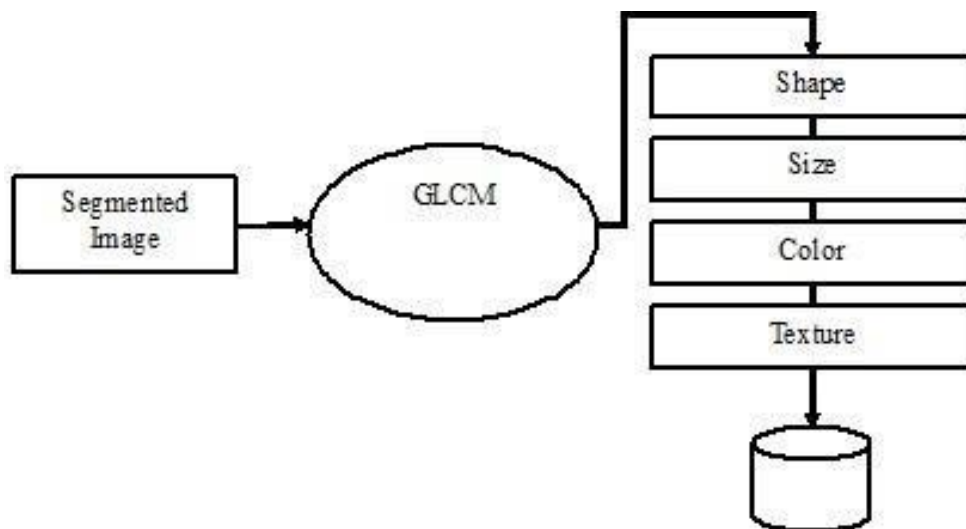


Fig. 5. Segemented Image Processing

Fig. 6. Face Categorization



mance. By adding the convolved grid of a vector-valued input to the kernel with a bank of filters to a specific layer, the CNN generates feature maps. The activations of the convolved feature maps are then computed using a non-linear rectified linear unit (ReLU). Utilizing local response normalization, the new feature map produced by the ReLU is normalized. (LRN). A spatial pooling approach is used to further compute the output from the normalization. (maximum or average pooling). Figure 6 shows the face categorization Module .

H. FACE IDENTIFICATION AND PREDICTION

The face detection module receives the facial image after it has been taken by the ATM Camera. This module finds areas of an image where people are most likely to be present. Following face recognition using RPN , the feature extraction module uses the face image as input to identify the most important features that will be used for classification. After that, the face image is categorized as known or unknown. If the image face is recognized, the appropriate Card Holder is found, and next step is taken. This module performs a matching procedure using test live camera-captured classified files and training classified results.

I. UNKNOWN FACE FORWARDER

An Unknown Face Verification Link will be established and delivered to the cardholder in order to certify the identity of an illegal user using some specific artificial intelligent agents for remote certification. This will either properly authorize the transaction or notify the banking security system of a security breach.

J. TRANSACTION

In this phase , the customer enters the amount for with- drawal and collects money from the the machine before expiry of 30 seconds.

K. PERFORMANCE ANALYSIS

Based on the context of this project, the key points associated with the performance indicators are discussed: True Positive (TP): The algorithms recognize the Card Holder and there is a Face. False Positive (FP): Although there isn't a Face, the algorithms identify the person as a Card Holder and display their name. False Negative (FN): Although a face exists, the algorithms fail to recognize the card holder's name and address. True Negative (TN): Nothing is being found and there is no Face. Figure 7 shows Performance Analysis Parameters.

	True (relevant)	False (not relevant)
Positive (retrieved)	TP	FP
Negative (not retrieved)	TN	FN

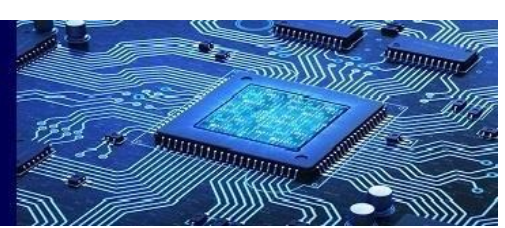


Fig. 7. Performance Analysis Parameters

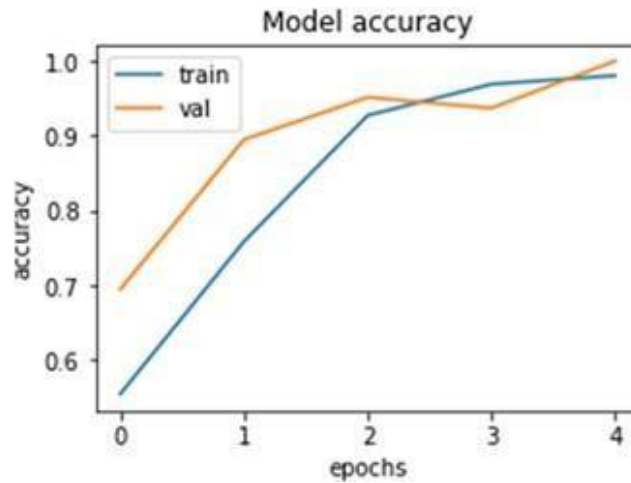


Fig. 8. Accuracy Plot

The accuracy, precision, recall and F1score for the training and validation obtained are detailed herewith a) Accuracy:0.9984025559105432 b) Precision: 0.9990234375 c) Recall: 0.9964285714285714 d) F1 score: 0.9977122020583142

Figure 8, 9 and 10 shows the plot for accuracy, precision and recall obtained for training and validation.

CONCLUSION AND FUTURE ENHANCEMENT

Biometrics offers the long-needed and greatly awaited so- lution to the issue of fraudulent transactions by identifying

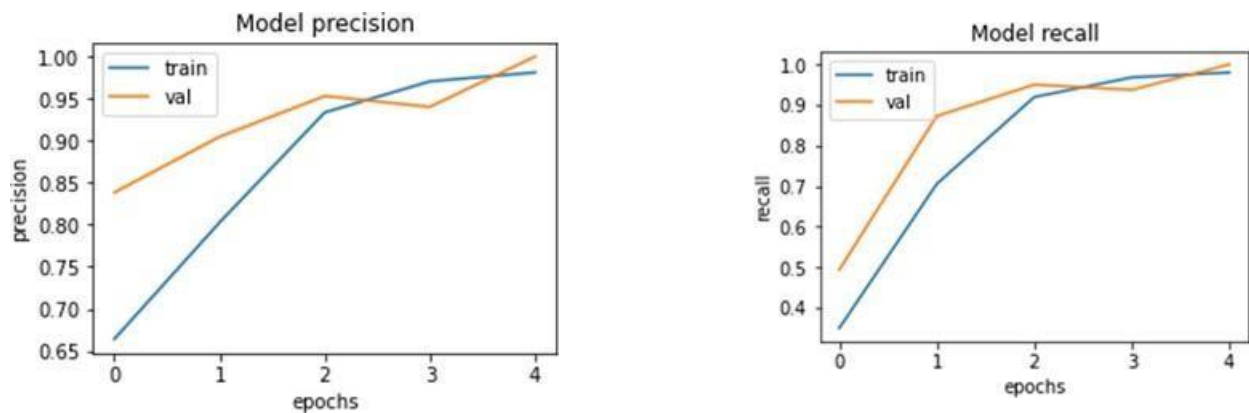


Fig. 9. Precision Plot

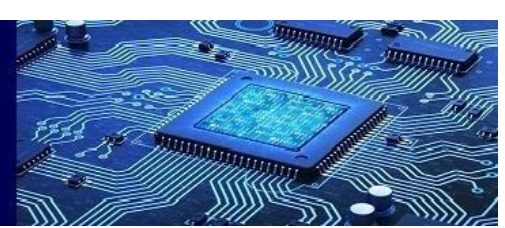


Fig. 10. Recall Plot

and authenticating account owners at the Automated Teller Machines. This project aims to propose a remedy for the dreaded problem of fraudulent transactions that can only be completed if the account holder is physically present or remotely present at an automated teller machine using biometrics and an anonymous face forwarder. As a result, it puts a stop to situations in which ATM locations experience illicit transactions without the real owner's knowledge. The efficiency of using one for identification is increased when another biometric attribute is utilized for authentication. The ATM security architecture accounts for potential proxy usage of data and security tools already in place, such as ATM Cards. All visible and accessible transactions are engaged in by the bank account owner in real-time.

Deep feature representation techniques should be developed in the future to further enhance recognition performance.

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