Face Boimetric Authentication System for ATM Using Deep Learning

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Abstract- Automated Teller Machines also known as ATM are widely usednowadaysby each and everyone.There isanurgent need for improving security in banking region. Due to tremendous increase in the number of criminals and their activities, the ATM has become insecure.

ATM systemstoday use no more than an access card and PINfor identity verification. The recent progress in biometric identification techniques, including finger printing, retina scanning, and facial recognition has made a great effort to rescue the unsafe situation at the ATM

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Keywords— "Biometric Authentication" ,"Automated Teller Machine (ATM)", "Deep Learning", "Convolutional Neural Networks (CNNs)","Facial Recognition","Security","FraudPrevention".

INTRODUCTION

Automated Teller Machines, popularly referred to as ATMs, are one of the most useful advancements in the banking sector. ATMs allow banking customers to avail quick self-serviced transactions, such as cash withdrawal, deposit, and fund transfers. ATMs enable individuals to make banking transactions without the help of an actual teller. Also, customers can avail banking services without having to visit a bank branch. Most ATM transactions can be availed with the use of a debit or credit card.

I. BACKGROUND

A.DEEPLEARNING

Deep learning attempts to mimic the human brain—albeit far from matching its ability—enabling systems to cluster data and make predictions with incredible accuracy. Deep learning is a subset of machine learning, which isessentially a neural network with three or more layers. These neural networks attempt to simulate the behavior of the human brain—albeit far from matching its ability— allowing it to "learn" from large amounts of data. While a neuralnetworkwithasinglelayercanstillmake approximate predictions, additional hidden layers can help to optimize and refine for accuracy. Deep learning drives many artificial intelligence (AI) applications and services that improve automation, performing analytical andphysical tasks without human intervention. Deep learning technology lies behind everyday products and services(such as digital assistants, voice-enabled TV remotes, and credit card fraud detection) as well as emergingtechnologies (such as self-driving cars).

B.REINFORCEMENTLEARNING

Data Collection: Gather a large dataset of facial images along with corresponding authentication labels (e.g., successful or failed authentication attempts). Ensure the dataset covers diverse demographics and variations in lighting conditions, angles, and facial expressions.Preprocessing: Clean and preprocess the facial images to enhance their quality and normalize factors such as lighting conditions and image orientation. This step may involve techniques like normalization, resizing, and alignment.Deep Learning Model Selection: Choose appropriate deep learning architectures for face recognition tasks,suchasconvolutionalneuralnetworks(CNNs).CNNs are particularly well-suited for image-based tasks and can automatically learn discriminative features fromraw pixel data.Model Training: Train the selected deep learning model using the preprocessed dataset. Utilize techniques like transfer learning if a pre-trained model is available to accelerate training and improve performance, especially with limited data. Validation and Testing:Validate the trained model using cross-validation techniques and evaluate its performance on a separate test dataset. Measure metrics such as accuracy, precision, recall, and F1- score to assess the model's effectiveness in authentication tasks. Predictive Analysis: Once the model is trained and validated, deploy it to the ATM system for real-time authentication

II. RELATEDWORKS

"Facial Recognition for ATM Security UsingConvolutional Neural Networks" by Saraf et al. In this work, the authors present a CNN-based facial recognition system designed specifically for ATM security. They evaluate the system's performance on real-world ATM authentication tasks and demonstrate its effectiveness in preventing unauthorized access."Deep Learning-Based ATMSecuritySystemUsingFacialRecognition"byLiuet al. This paper proposes an ATM security system that employs deep learning for facial recognition. The authors develop a CNN model trained on a large dataset of facial images to authenticate users at ATMs, enhancing security and user convenience."Enhancing ATM Security Using Deep Learning-Based Face Recognition" by Sharma et al. This study investigates the use of deep learning-based face recognition for enhancing ATM security. The authors develop a robust authentication system based on CNNs, addressing challenges such as illumination variations and occlusions in facial images."Face Recognition for ATM Security: A Survey" by Gupta et al. This survey paper provides an overview of face recognition techniques usedin ATM security systems. It covers traditional methods as well as recent advancements in deep learning-based approaches,discussingtheirstrengthsandlimitationsinthe context of ATM authentication.

III. EXIXTINGSYSTEM

Existing ATM authentication method is the use of password-PINs and OTP. Presently, ATM systems use no more than an access card which usually has a magnetic stripeand a fixed Personal Identification Number (PIN)for identity verification. Some other cases utilizea chip and a PIN which sometimes has a magstripe in case the chip fails as a backup for identificatiopurposes. QR cash withdrawals were enabled so customers could ditch their ATM cards and simply scan AQR-code on ATM using the QR app to withdraw cash A QR code

scanner is required to detect code and decrypt information in stored in QR code. Scanner need to be installed in the ATM machine to take input credentials from the user.

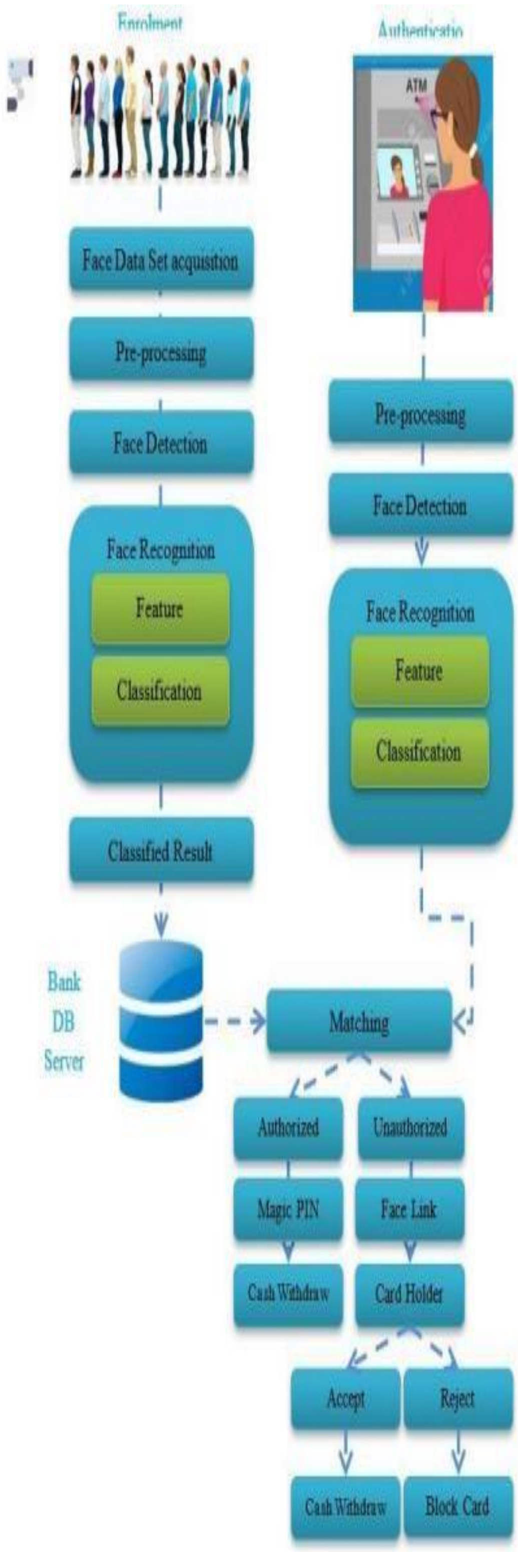
IV. PROPOSEDMETHODS

This project proposes an automatic teller machine multi modal securitymodel that would combine a physical access card and electronic facial recognition using Deep ConvolutionalNeuralNetwork. Facial Biometric Authentication System using Deep Learning Techniques Deep learning is a subset of machine learning, which, in turn, is a subset of artificial intelligence (AI). When it comes to Face recognition, deep learning enables us to achieve greater accuracy than traditional machine learning methods its proper location.

Deep FR system with face detector and alignment. First, a facedetectorisusedtolocalizefaces.Second,thefacesare aligned to normalized canonical coordinates. Third, the FR module is implemented. In FR module, face antispoofing recognizes Whether the face is live or spoofed; face processing is used to handle variations before training and testing, e.g. poses, ages; Different architectures and loss functions are used to extract discriminative deep feature when training; face matching methods are used to do feature classification after the deep features of testing data areextracted.UnknownFaceVerificationLinkGenerator

When the stored image and the captured image don'tmatch, it means that he is an unauthorized user. Face Verification Link will be generated and sent to user to verify the identity of unauthorized user through some dedicated artificial intelligent agents, for remote certification, which either authorizes the transaction appropriately or signals a security-violation alert to the banking security system

SYSTEMARCHITECTURE



VII. RESULT

Here, we count some results obtained by knowledge distillation in the field of target detection. The datasets VOC07+12 and MSCOCO. VOC and COCO are commonly used for target detection and image segmentation.VOC 07+12 has 20 object categories, COCO contains 164K images, and COCO has 80 object categories, which are challenging and authoritative. The detection network is the classical two-stage algorithm FasterRCNN, where the teacher-student backbone network is either a resnet101-resnet50 combination or a RetinaNet101-RetinaNet50 combination. We summarize the results of knowledge distillation for target detection over the past 5 years, and we compare the advantages and disadvantages of each distillation method from a fair perspective. From the table below, we can clearly see that knowledge distillation can significantly raise the performance of minimodels without changing the structure of the network, and knowledge distillation can make a great contribution to the deployment of future projects. From the data in the tables, we can find that there are three types of knowledge that can be used for knowledge distillation, feature-based, response-based, and relationshipbased knowledge. In our perception, the images are background except for the detected objects, and the computation of background features wastes a lot of computational resources and seriously affects the detection performance, but found that background features are also helpful for detection performance, and in addition, current knowledge distillation methods ignore the role of categories outside the dataset for target detection, and arbitrarily discarding background features is an unwise choice. The intermediate layer features utilized in knowledge distillation want to prefer the student feature maps to be as similar as possibletotheteacherfeaturemapsbycalculatingadistance between the feature maps and adding the distance values to the loss function and thenusing backpropagation to improve the degree of similarity between teacher feature maps and student feature maps. Response-based knowledge is for students to imitate the soft output of the teacher's network, using additional information about the similarities withinand between classes, which is the simplest and mostefficient way to handle this, but this would be missing the supervisory information in the middle layer, which is not a very significant performance gain for the student network. The most commonly used in current knowledge distillationis the combination of featurebased and response-based knowledgeRelationship-based knowledge]is an extensionof response-based knowledge and feature-based knowledge, and it studies the relationship between different layers and samples more comprehensively and deeply.

VIII. CONCLUSIONAND FUTUREWORK

Face Biometrics as means of identifying and authenticating account owners at the Automated Teller Machines gives the needed and much anticipated solution to the problem of illegal transactions. In this project, we have developed to proffer a solution to the much-dreaded issue of fraudulent transactions through Automated Teller Machine by biometrics and Unknown Face Forwarder that can be made possible only when the account holder is physically or far present. Thus, it eliminates cases of illegal transactions atthe ATM points without the knowledge of the authentic owner. Using a biometric feature for identification is strong and it is further fortified when another is used at authentication level. The ATM security design incorporates thepossibleproxyusageoftheexistingsecuritytools(such as ATM Card) and information (such as PIN) into the existing ATM security mechanisms.In the future, the recognition performance should be further boosted by designing novel deep feature representation scheme

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