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ENRICHING BIOMETRIC ATM OPERATIONS THROUGH DEEP LEARNING

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ABSTRACT

Biometric authentication techniques are becoming more and more prevalent in various implementations, relying on fingerprints and facial features of individuals. Although there are numerous facial recognition systems available. Further research is needed to uncover factors that can enhance efficiency and accuracy. Facial and fingerprint identification are crucial in the identification process due to their ability to operate independently without human intervention, unlike certain other biometric methods. This not only demonstrates the immense potential for enhancing security in Virtual ATM transactions, but also sheds light on the reasons behind thesignificant interest in biometric identification systems. Thus, a proposed framework has been developed to enhance biometric authentication on Virtual ATMs by utilizing features like Facial and Fingerprint recognition. The framework incorporates Live Streaming and Region of Interest, along with Channel boosted Convolutional Neural Networks. Additionally, OTP authentication hasbeen implemented. The framework has been extensively tested through thorough experimentation to yield very promising results.

Keywords: Channel Boost Convolution Neural Network, Deep Learning, Bio Metric ATM Machines, Face Recognition, Finger Print Authentication.

I. INTRODUCTION

India has seen the introduction of various types of equipment due to technological advancements, all aimed at enhancing customer satisfaction. An item that greatly improved banking for financial institutions was the automatic teller machine (ATM). With the introduction of ATMs, customers gained the ability to carry out financial transactions on their own. Initially, only customers of a specific bank had access to an ATM for transferring funds. However, over time, all ATMs became interconnected through a unified network, allowing customers from any bank to conveniently use any ATM they prefer. Thanks to this, customers of other banks were still able to use the ATMs of other banks for their banking needs, including making deposits, withdrawals, and wire transfers.

Facial detection comes naturally to human beings, to the point where even newborns can distinguish between family members and friends. Nevertheless, face detection poses a challenge for computers. In the first automated face identification system, a set of facial landmarks such as the eyeballs, eyebrows, and chin are labeled to create extracted features. Faces are then identified by calculating the Euclideandistance between the extracted features from different photos. Many methods use feature maps of different dimensions to analyze the architectural aspects of facial photographs in a large database. Similar to an IT project manager, some face recognition methods streamline the categorization process by treating the face region as a junction and representing it in a lower-dimensional environment derived from the input images' multidimensional space.

Facial identification has been extensively researched in recent years as a highly reliable method for establishing a person's identification. Face recognition from photographs is awidely explored field in biometrics. One of the valuable applications of facial recognition and identification technologies is the assessment of images for interpretation. Facial recognition software has caught the attention of mental health professionals, neuroscientists, and machine learning experts. They are intrigued by the potential insights it may offer into the workings of the human brain. In today's world, biometric identification methods such as fingerprint and retinal scanners have become quite common. However, it is important to note that these methods still require human verification. However, it is not required to use face pictures for person authentication. Facial recognition technology is essential for establishing a person's identity, as it eliminatesthe need for human cooperation, making it a superior biometric approach.

II. LITERATURE SURVEY

1. According to Joseph A. Mensah et al., despite the advancements made in deep learning face recognition algorithms, the majority of face recognition algorithms still perform poorly in a variety of limited situations, such as occlusions and expressions. The study assessed the effectiveness of the Face Net deep learning model for face recognition under the aforementioned constraints and when three (3) statistical multiple imputation methods (Multivariable Imputation using Chain Equations (MICE), Miss Forest, and Regularized Expectation Maximization (RegEM)) are adopted for occlusion recovery using expression variant test face images that were artificially occluded at 30% and 40% rates. The study's findings demonstrated that the algorithm's recognition rates were higher when imputation- based recovered faces were utilized for identification as opposed to their multiple constrained counterparts. Nonetheless, the FaceNet deep learning algorithm demonstrated superior recognition accuracy for test faces that were reconstructed using the MissForest imputation method. Moreover, the investigation showed that a few basic augmentation techniques were adequate to improve the FaceNet model's performance even more. In particular, FaceNet algorithms yielded the highest average recognition rates (85.19% and 79.5% for 30% and 40% occlusion levels, respectively) when used with MissForest as the de-occlusion mechanism under augmentation scheme IV, which included slight rotations, horizontal flipping, shearing, brightness adjustments, and stretching. The study also discovered that, when it came to classification under augmentation scheme IV, there was no difference in performance between Support Vector Machines (SVM) and City Block (CB). For moderately high obstructed test faces with a range of expressions, the study suggests applying the MissForest imputation method to improve the FaceNet face recognition model's performance.
2. Garcia-Gonzalez Daniel et al. In the scientific community these days, human activity recognition (HAR) is one of the hottest topics. An increasing number of researchers are choosing to contribute in this field due to the low cost, high accuracy, and ease of use of the sensors from various wearables and smartphones. But all of the research done in this area up until very recently was done in lab settings, with very little in common with the authors' everyday lives. This essay will concentrate on the recent trend of applying all of the previously learned material to a real-world setting. In light of this, a dataset that had previously been released was used. This paper attempts to identify the various actions that are researched there in this manner. This research investigates novel models' designs and architectures, influenced by the models that have produced the greatest results in the literature,in order to carry out this classification.
3. Faizabadi Ahmed Rimaz et al. Retraining or fine- tuning of Face Recognition (FR) models causes an undesired downtime for FR applications in the open world or adapted area. It's possible that threshold setting techniques like σ values won't work as well if lowcost O (1) is used. An FR application's security is likewise jeopardized by the use of such predefined threshold values. Thus, a dynamic ROI-based threshold adaptor algorithm was used in this paper to suggest an adjustable threshold. The optimal threshold's search space is reduced by the suggested strategy, which also speeds it up by 12 times over using traditional techniques. enabling the setting of thresholds in real-time. Using two assessment datasets, the author showed that the suggested approach greatly enhanced five cutting-edge deep FR models, producingthe best results. Furthermore, in the open world FR application, there are very few positive pairs. Therefore, taking the F1-score into account is essential. According to the suggested approach, a more useful criterion for performance benchmarking in open-world FR applications is accuracy at the highest reported F1-scores.
4. This research paper's second section, known as the literature survey, is devoted to a review of earlier works. Additionally, a general description of the implemented approach is provided in the section Proposed methodology, which contains three sections. In Section 3, the experiment's results are examined. This study concludes with Section 5, which offers opportunities for future development.
5. P. Archana together et al. proposes the goal of this research is to lower the risk associated with car theft. Therefore, the author has designed in order to overcome these difficulties. The following describes the project's scope: record faces of people with a webcam, Compile a dataset for AI training. Identify a person by analyzing facial data on a bank server. If both data match, a person will be able to employ MLand AI to limit

card access so that only approved individuals who have been recognized by a facial recognition algorithm are permitted to complete the transaction. Should there be a discrepancy in the data, an email will be sent to the individual whose email address is on file with the bank. Additionally, thetransaction will be rejected.

6. C. Ranjeet Kumar et al. talk about Nowadays, facial recognition technology is commonplace and not only a cuttingedge innovation. Around the world, it has been applied to several security and profiling applications. In the 1960s, the first face identification models were created and were only intended to categorize images of individuals. Face recognition models have been refined and redesigned over the previousfew decades to recognize every person in every frame of real- time, high-definition video input. It still has a great deal of potential uses, and it can be further refined for extreme precision by employing various strategies. The authors of this study used two distinct methods for facial recognition. The first method uses a CNN to identify important features in a picture and then classifies it with a KNN algorithm. The input image is classified using a Siamese network in the subsequent method. Training and data collecting are the main topics of thefirst section. The application of these strategies is explained in detail in the section that follows. Additionally, the effectiveness of various methods was assessed and best shown.
7. Abdullahi Sunusi Bala et al. describes For biometric recognition, it was discovered that the multimodal biometric fingerprint and vein deep learning features now in use work well. However, the extracted features can obscure some important information due to irrelevant picture features, and the current effectiveness of the deep learning features is limited due to missing temporal image dependencies. A series of filtered spatial and temporal multimodal fingerprint and finger vein network sequences (FS-STMFPFV-Net) are proposed in this work. To improve image variabilities, two- channel independent learning is used to create the overall suggested FS-STMFPFV-Net. The fingerprint and finger vein images are aligned together inside the image generator to create the image sequence in the first channel. To extract spatial sequence-wise information, the sequences are incorporated into a deep convolution neural network fusion model's five layers.
8. Banerjee Debdeep et al. have increased the testing efficiency thanks to the implementation of the 3D face authentication test automation. The author took into account a number of test scenarios and gathered test results on a 3DFA end-to-end application from testing on facial appearance, device motion, and angular position. The hardware-accelerated 3DFA solution and third-party solutions were also compared using this automated test system by the author, who found that there was a 23.9% difference in facial authentication latency when the user ran motion test scenarios. It has been demonstrated that test automation is more dependable and effective than manual face authentication testing. It is simple to benchmark different performance attributes across several 3D face authentication software application products using this test technique. Alassafi Madini O. et al. This work proposes a hybrid face PAD approach that combines a MobileNET CNN's transfer learning with the idea of interpolation-based image diffusion. On the Replay-Attack, Replay-Mobile, CASIA- FASD, and ROSEYoutu databases, the suggested architecture has demonstrated encouraging results, achieving the highest accuracy and HTER of 99.93% and 0.09%, 99.04% and 1.14%, 99.90% and 0.09%, and 95.04% and 4.92%, respectively. Additionally, the suggested approach performed better in cross-domain evaluation. Such face PAD approaches have a wide range of applications. As for the author's future plans, they plan to integrate their face PAD method with a facial recognition and gesture recognition system for monitoring student attendance and exams in an educational setting. This will create a deep learning-based framework that will support the daily operations of schools.
9. Zhang Xinman et al. This study presents the development of an effective multimodal biometric authentication system using speech and face biometrics, based on Android. To reduce the time and space complexity in this system, an enhanced LBP coding-based feature extraction method is implemented. In order to reduce the misjudgment ratio for the voice endpoint, eliminate the invalid voice segment, and increase algorithm effectiveness in the low SNR condition, the author also presents an enhanced VAD approach. The author presents an adaptive fusion strategy to implement multimodal biometric fusion authentication, which effectively improves authentication performance by addressing the limitations of unimodal biometric authentication. This strategy takes into account the hardware performance of the Android-based smart terminal. The outcomes of the experiments demonstrate that the created

authentication system is capable of effectively implementing identity identification in a variety of scenarios and achieving high-security application management. There are still certain drawbacks with the established multimodal authentication method, despite its many benefits.

10. Joseph Michael et al. Numerous challenges related to face identification were addressed by the system used inthis study, including the presentation of faces in various scales, variations in stance, variations in facial emotions, uncontrolled lighting, and background. Pre-processing tackles a few of these issues, while the model tackles the rest inaccordance with the biological inspiration. The idea behind the model stems from the discovery that an end-to-end, holistic neural network processing images enables the network to adopt an internal representation while preserving similarity information. When combined with the configural information, the resulting network achieves very high accuracy in predicting unseen profile photographs. The study conducted in this work yielded definitive results about the efficiency of computational learning models that execute face recognition intwo steps, akin to the human visual cortex's two-step processof holistic processing and recognition. It also examined how the explicit application of CI affected the facial recognition procedure.
11. Moolla Yaseen et al. The author described biometricdevices that use an infant's fingerprint, irises, and outer ear shape to identify them. Every modality has unique advantages and disadvantages. It has been discovered that ear biometrics are simple to learn from birth and that algorithms designed for adult ears may also be applied to the ears of infants. The authors have demonstrated that it is feasible to create a hardware tool that takes fingerprints from infants as early as six weeks of age, and to save the fingerprint data in a manner that can be used with currently available fingerprint comparison software. Additionally, the authors have demonstrated that the acquisition rate increases with age and that iris biometrics can be used to match people as early as six weeks. Suggestions were made for how to integrate these modalities in subsequent research in order to develop more reliable and accurate biometric identification systems for newborns and to expand the useful life of these systems from birth to adulthood.
12. Supphachoke Suntiwichaya et al. Wenqing Yan et al. The author's research aims to remind people to wear face masks when they walk outside since a facial image detection and classification method will be utilized for authentication and authorization since the coronavirus disease 2019 (COVIDE-19) outbreak has spread throughout the nation. This work has demonstrated how the author's CNN-based models can identify gender, mask wearer status, and glasses wearer status via comparison between two models.Created a mixed public dataset model using the author using AFW, MAFA, and WIDER FACE.Additionally, the author pre-trains the model for the advance detection rate using VGG-Face.
13. Mun, Hyung-jin, et al. Deep learning-based image identification technology has advanced recently, and home services and security systems that use biometric data—like fingerprints, iris scans, and facial recognition—are gainingpopularity. Specifically, a great deal of research has been doneon face recognition-based user authentication techniques. This paper provides a camera and Jetson Nano-based CCTV visitor authentication system. CCTV is used to gather face data with seven attributes that can be used to identify a person duringthe preprocessing stage of face recognition. Deep learning is used to identify facial features in the gathered dataset after it has been annotated for classification. The image data is deemed to be human if one or more identified features are present, and 81 feature vectors are used to match the visitor's face in detail with user data that has been stored.

III. PROPOSED METHODOLOGY

The proposed method for implementing a Cardless biometric ATM system that incorporates biometric authentication through face and fingerprint recognition is illustrated in figure 1 above. The following steps outline the process of achieving this system.

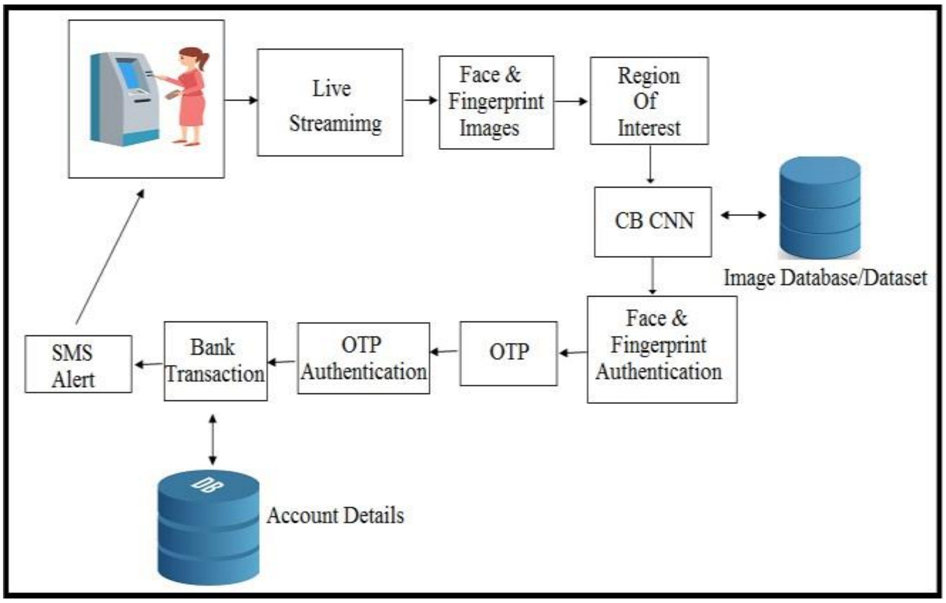

Figure 1: System Overview

Step 1: GUI Building - To showcase our methodology, we have developed an interactive user interface using the swings framework in the java programming language. The application for performing bank transactions by the customer has been developed with a user-friendly interface that is intuitive and simple to navigate. The interface has been developed and designed to make it easy for users to enroll in the platform. It collects various attributes and information, such as name, date of birth, and mobile number. Additionally, it includes user authentication components like face and fingerprints. User characteristics, such as facial features captured during registration, are stored along with the user's fingerprints. These qualities are valuable for implementing the biometric ATM approach, which will authenticate users using facial features and fingerprints. The unique attributes of the individual users are organized and saved in an image database, which will be used in subsequent stages to train our deep learning model.

Step 2: Training the channel boost Convolution neural network model– Collecting images of the user's face and fingerprints has been essential for training the chosen deep learning model in this implementation. The CB-CNN model isbeing used to train and recognize the user through their face and fingerprints.

The CB-CNN, or Channel Boosted Convolutional Neural Networks, represents a significant advancement over the conventional Convolutional Neural Networks. The CB-CNN model uses boosted color channels for implementation, unlike the conventional CNN which does not include any boosted channels. Implementing boosted channels in the CB-CNN approach can greatly enhance recognition accuracy when compared to the traditional CNN.

Developing sequential neural network architectures is made possible by the Sequential class in the TensorFlow library. Additionally, in the initial phase of the CB-CNN Design, a convolution layer is incorporated. This layer consists of 32 3x3 kernels and utilizes the ReLU activation function. It is specifically designed to accommodate images ofthe appropriate dimensions. Ensuring that the images are of the same size is the sole purpose of this layer. Next, a Convolution layer is introduced with 64 3 x 3 kernels and ReLU activation. A maxpooling layer with a dropout rate of 25% and a size of 2 by 2 units has been planned.

With a size of 3 by 3 for each of the 128 kernels, this is made possible by the inclusion of extra fully connected layers. We have utilized a unique activation function known as the ReLU activation function. The size of the maximum pooling layer has been set to 2x2. Once the third layer is finished, the final layer is set up using 128 3x3 kernels and the ReLU activation function. Adding a second Max pooling layer, we make a slight adjustment to the dropout rate, setting it at 25%, while maintaining the dimensions at 2 x 2. Once the neural network training is finished, it undergoes flattening through the flatten method. A dense layer with a size of 1024 is then applied, along with the ReLU activation function. We need a dropout ratio of 50% at the end of the convolution neural network. After that, a dense layer has been added with 7 classes, representing the 7 users used in this methodologydemonstration.

Utilizing the Adam optimizer and running 500 epochs, all user attributes, including their face and fingerprints, are improved during the learning phase. Once the training stage is complete, the model retrieves the acquired data from an H5file and applies it during the testing phase. Figure 2 displays the structure of the Channel Boosted – Convolutional Neural Network.

Layer	Activation
CONV 2D 32 X 3 X 3	Relu
CONV 2D 64 X 3 X 3	Relu
MaxPooling2D 2 X 2	
Dropout 0.25	
CONV 2D 128 X 3 X 3	Relu
MaxPooling2D 2 X 2	
CONV 2D 128 X 3 X 3	Relu
MaxPooling2D 2 X 2	
Dropout 0.25	
Flatten	
Dense 1024	Relu
Dropout 0.25	
Dense 7	Softmax
Adam Optimizer	

Figure 2: CB- CNN Architecture

Step 3: User Authentication and Transaction Completion

The model trained in the previous step is being used to authenticate the user and complete the transaction. The user interacts with the virtual ATM to provide the necessary details, such as face and fingerprint, for verification purposes. The system captures facial and fingerprint images and passes them on to the following modules for authentication purposes.

The system uses the images by initially evaluating the regions of interest in the images. The region of interest focuseson isolating the facial region and fingerprints for evaluation bythe trained model. The images are then processed by the convolutional neural network-based face identification system, as follows. It is easy to examine the performance metricsbecause of the mistake that the method for accurately identifying the user's face achieves.

The Root Mean Square Error, or RMSE, is used to make it possible to calculate the error that the method that is being presented achieves. The accuracy of the proposed strategy's performance is demonstrated by the inaccuracy of the previously proposed CB- CNN-based face identification method. The RMSE approach simplifies the error evaluation between two continuously correlated metrics. The degree of face identification accuracy and inaccuracy are the criteriataken into consideration for this procedure. After these data have been evaluated, equation 5 is used to calculate the error.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(x_{1,i} - x_{2,i}\right)^2}{n}}$$

Trained model to authenticate the user using the captured facial 1)and fingerprint images.

After the user has been verified, a One Time Password (OTP) is generated and then sent to the user through email. Please authenticate this OTP before proceeding with the transaction. Once the OTP is authenticated, the system smoothly guides the user through the bank transaction process for maximum efficiency.

IV. RESULTS AND DISUSSIONS

The proposed approach involves utilizing the facial and fingerprint characteristics of the user to create a biometric ATM. Both Python and Java programming languages have already embraced the concept, with the help of the Spyder and NetBeans integrated development environments, respectively. The code was written in

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both of these situations. The plan involves utilizing the OpenCV, TensorFlow, and Kerasframeworks to perform the required tasks of deep learning.For testing the forthcoming implementation, it was found that a laptop with an Intel Core i5 CPU, 8 GB of Memory, and 1 TB of storage space was the most suitable choice.

Measuring the accuracy of face and fingerprint detection requires considering the efficiency of the proposed technique. The level of error can be a useful indicator of the reliability of a technique. Generally, a lower error rate suggests a higher level of trustworthiness. An accurate error analysis can be conducted by utilizing the root mean square error measure.

Performance evaluation based on RMSE

Several studies have been carried out in order to quantify the error generated by the channel boost

Where,

$\sum$ - Summation

$(x1 - x2)^2$ - Variations Squared for the total of the differences between the number of face identifications that were obtained and those that were anticipated

n - Number of Trails

10 different users, each completing 10 trials on the system with a different set of facial expressions, are used to measure these two variables. Table 1 is shown below and contains thetrial results.

Table 1: Mean Square error measurement

User no	No of Expected Face Identification	No of obtained Face Identification	MSE
1	10	8	4
2	10	9	1
3	10	7	9
4	10	10	0
5	10	10	0
6	10	7	9
7	10	8	4
8	10	9	1
9	10	9	1
10	10	10	0

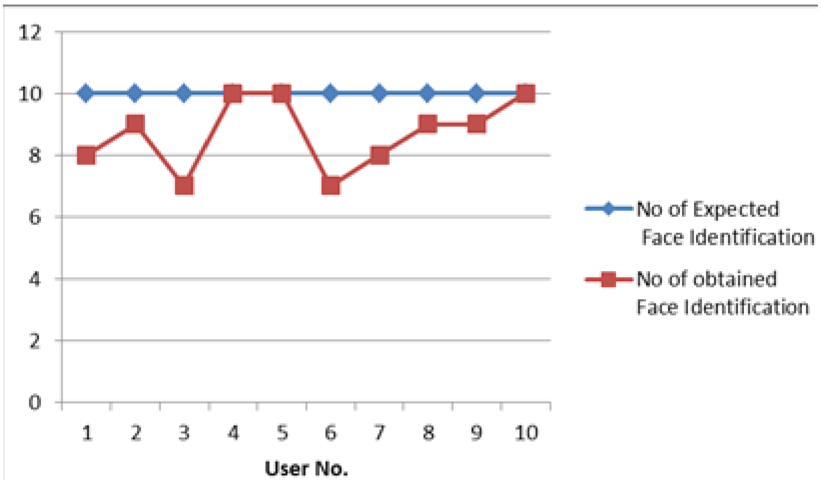

Figure 3: Comparison of MSE in between Expected No of face identifications V/s obtained No of face identifications

The graphical depiction of the error rate, as illustrated in Figure 3, has been facilitated by the outcomes of the experimental assessment of the approach. The graph illustrates the algorithm's minimal level of inaccuracy in interpretingusers' facial features to determine their identity. The enhanced detection accuracy is attributed to the highly precise implementation of the Channel boost Convolutional Neural Network. The decision making process enhances the results,as demonstrated by the MSE and RMSE values of 2.9 and 1.702, respectively. This

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evaluation demonstrates the level of precision and accuracy with which the facial recognition technique was developed for the purpose of Biometric ATM.

Performance Evaluation based on Precision and Recall

To evaluate the comprehensiveness of a particular paradigm module's execution, measures of recall and precisionare highly helpful. We cover these two metrics in the broader context of our method. The precision of the module, which encompasses its reliability throughout a large range, defines itsrelative correctness.

We compared the amount of successful identifications to the overall number of tests to find out how accurate this method was. Still, when figuring out how reliable the CB- CNN component is as a whole, the recall requirements are a helpful supplement to the accuracy evaluation. The reason behind this is that precision monitoring alone is insufficient. By comparing the percentage of right to wrong identifications,the recall can be found using this technique. Here are some formulae to help you put a number on this argument.

The following is an illustration of precision and recall:

A= The value of A is the sum of all correct finger printidentifications.

B= The quantity of incorrect finger print identifications isdenoted by B.

C= This is the total number of incorrect finger printidentifications.

So, precision can be defined asPrecision = (A / (A+ B)) *100 Recall = (B / (B+ C)) *100

The results of the experiment are displayed in Table 2 below, using the formula described before. Figure 4 shows theresult that can be obtained using these statistical parameters.

Table 2: Precision and Recall Measurement Table

No. of trails	Accurate Finger Print Authentication (A)	Inaccurate Finger Print Authentication (B)	Accurate Finger Print Authentication Not Done (C)	Precision	Recall
5	5	0	0	100	100
10	8	2	0	80	100
15	12	3	0	80	100
20	18	2	0	90	100
25	22	3	0	88	100

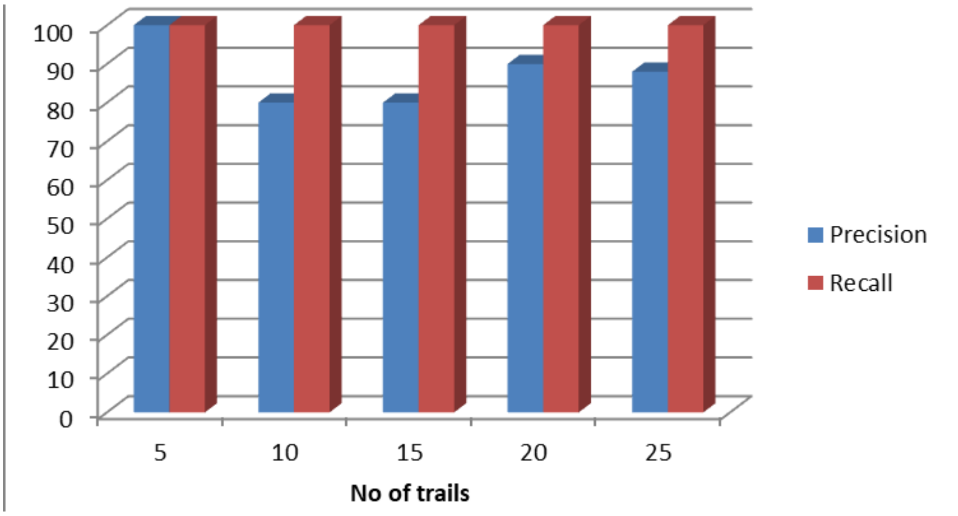

Figure 4: Precision and Recall estimation

This graph showcases the impressive capabilities of the CB-CNN, showcasing its ability to handle a wide range of trial counts and accurately detect finger print based on the input data. The method's reliability is evident from its impressive accuracy and recall rates of 87.6 and 100 percent, respectively.The numbers are impressive for the initial implementation of this technique, and the resulting success is praiseworthy.

V. CONCLUSION

In this research article, the we have presented a detailed approach for implementing a Cardless biometric ATM system that incorporates biometric authentication through face and fingerprint recognition. The proposed method utilizes an ATMmachine in conjunction with a camera to capture the live feed of the user. The live feed from the ATM camera is being streamed to the system in real-time, allowing for the capture ofthe user's face and fingerprints. These images are transformed and passed on to the next stage to estimate the region of interest. It focuses on isolating the facial features and thespecific area of the image that contains the face. The Channel Boosted Convolutional Neural networks are connected to a database that contains user facial and fingerprint images. The CB-CNN approach efficiently verifies the user's identity by using the images in the database, and a One Time Password is sent to the registered user's mobile number. Once the user enters the OTP, it undergoes authentication to verify their identity. If successful, the user is granted permission to carry out the bank transaction at the ATM. Additionally, a relevant alert is promptly sent to the user via SMS. The approach has been thoroughly evaluated for its performance using RMSE, Precision, and Recall, resulting in highly reassuring measurements.

VI. FUTURESCOPE

In the future, accurate recognition of aging faces can be achieved by implementing the Reinforcement learning model.

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