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Secure Banking Based on Machine Learning Based IRIS Pattern Recognition

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Abstract: Authentication in ATM by iris pattern is all concerning preventing fraudulent activities and to conjointly produce a lot of security in authentication, to the existing system by utilizing of iris recognition. With this system, eye image of a bank user is captured at the initial registration process from that the iris image is extracted from the image by Hough's algorithm and Canny edge detection algorithm. if an illegal activity of trying to access someone account, officials will use the iris featured for the illegal transaction is then compared (example: Aadhar card Database) Government database details to find the criminal. Iris recognition, identifying and verification are programmed process that utilizes mathematical pattern-recognition systems on video to catch a human eye, where muddled irregular patters which are one of a kind, can be seen from some distance by camera.

An important feature of iris recognition is its speed of coordinating and its compelling immunity to recognition of false images. It is the strength of the iris as an internal, ensured, yet remotely noticeable organ of the eye. Deep learning is right now a to a great degree dynamic research field in machine learning and pattern recognition society. Deep learning has increased immense success in an expansive zone of applications, for example, speech recognition, computer vision, and natural language processing. With the sheer size of information accessible today, big data brings huge open doors and transformative potential for different areas; then again, it likewise displays extraordinary difficulties to harness information and data. As the information continues getting greater, Deep learning is coming to play a key part in giving big data predictive analytics solutions. This paper shows a brief outline of Deep learning and highlight how it can be adequately connected for optical character recognition in iris.

Keywords: Iris recognition, Houghs algorithm, canny edge detection, GPU Optical Recognition, security in ATM's, Feature Representation, Neural Networks, Deep Learning and Machine Learning.

1. INTRODUCTION

Biometric based ATMs are utilized for extensive variety of uses, for example, for Banking, Self-administration and ATM. Biometric ATMs offer a kind of interface with no less than one Biometric catching gadget like Fingerprint scanner, Iris camera, Palm/Finger vein scanner which are for the most pattern recognition identifier. They are regularly called as Biometrics ATM, Wall Mount Biometrics ATM, and Biometrics Device/Machine. The majority of the ATM in the past have been utilizing ID cards to recognize clients but since numerous new age threats, another era of Biometrics ATM are being sent for ATMs that are associated with Large Computer CPU and Memory that give adequate handling capacities to bolster top of the line Biometrics Verification or Identification and recognition System. Despite the fact that numerous organizations keep on producing different smart card applications and promoting arrangements to showcase the shrewd card, the mass purchaser's acknowledgment and use is still yet to be accomplished.

Organization's particularly budgetary establishment has been putting a great many dollars in the new innovation framework with the desire that it will add to the general gainfulness and piece of the overall industry. Deep Learning is a branch of artificial intelligence that has been presented with the goal of taking machine learning nearer to Artificial Intelligence which prompted high achievements in speech recognition, pattern recognition and automated image. As of late, there's been resurgence in the field of Artificial Intelligence. Past scholastic world it spreads with real players like Google, Facebook, Microsoft and so on having their own examination group to make some amazing acquisitions.

This resurgence has been controlled into another pattern in machine learning AI, known as "Deep Learning". In this paper, the key ideas required and important algorithms for Deep learning, with the least complex unit of composition as its commencement are advised. What's more, how it will be connected for optical pattern recognition was additionally talked about in this paper.

Big Data the substantial volumes of information that are currently created in numerous fields can display issues in storage, processing and transmission. But their analysis may produce some significant information and useful insights.

Data Interpretation: The Deep Learning system has strengths in areas such as information retrieval, parsing, pattern recognition, and processing of large data. The Deep Learning framework has qualities in ranges, for example, data recovery, parsing, pattern recognition and data processing.

Data Velocity: The Deep Learning framework fits an incremental style, data was absorbed as it is gotten, much as individuals do and the streaming data has been analysed..

Data Volume: It's the component of making Big Data smaller. Accurately, diminishing the measure of big data by means of lossless compression can yield direct advantages in the administration, stockpiling and transmission of information, and aberrant advantages in a few of alternate territories talked about in this article.

2. OBJECTIVE

This Biometric system is proposed for secure remote ATM transaction, also to prevent fraudulent activities by detecting and identifying the person automatically by analyzing the iris. Once a user is about to do a transaction his iris is scanned and compared with the original one which is captured at the time of registration of the user with the bank. For recognition of the iris from millions of available user deep learning concept is involved to make the authorization much more effective and faster. By using iris as a security we can make sure no fraudulent transaction can be made unless the genuine user or a member associated to the account appears in front of ATM machine to do the transaction.

3. EXISTING SYSTEM

The existing ATM machine has generated a great deal of interest due to the importance and practical implications of the problem. In this system, the individual who wants to perform transaction at the transaction terminal will insert his credit/debit card to perform transaction and enter his/her 4-digit PIN number. The user is authenticated by verifying his/her PIN number with the database and then permits the user to perform transaction. Major disadvantage of this system is that anyone who has the card and knows the ATM pin can perform transaction. By this it is prone to fraudulent transactions by theft of ATM cards and then he can withdraw cash from others account.

4. PROPOSED SYSTEM

The proposed system overcomes the disadvantages of existing system by verifying the individual's iris by matching it with the database as well as the pin number of the credit/debit card of the individual and a onetime pin will be generated which will be sent to the registered mobile which the user must enter. So this will check the card holder as well as his credit/debit card. In wording, the potential advantages of this Deep Learning System, with big data concepts are connected in the accompanying zones: Variety of the problem in big data: Fitting different configurations of learning, and their assorted methods of processing, utilizing a general structure for the representation and knowledge processing..

5. SYSTEM ARCHITECTURE

A system architecture or frameworks model is the conceptual model that characterizes the structure, behavior and more perspectives of a system. This model demonstrates the working stream of the framework with different parts enjoyed working of this smart ATM.

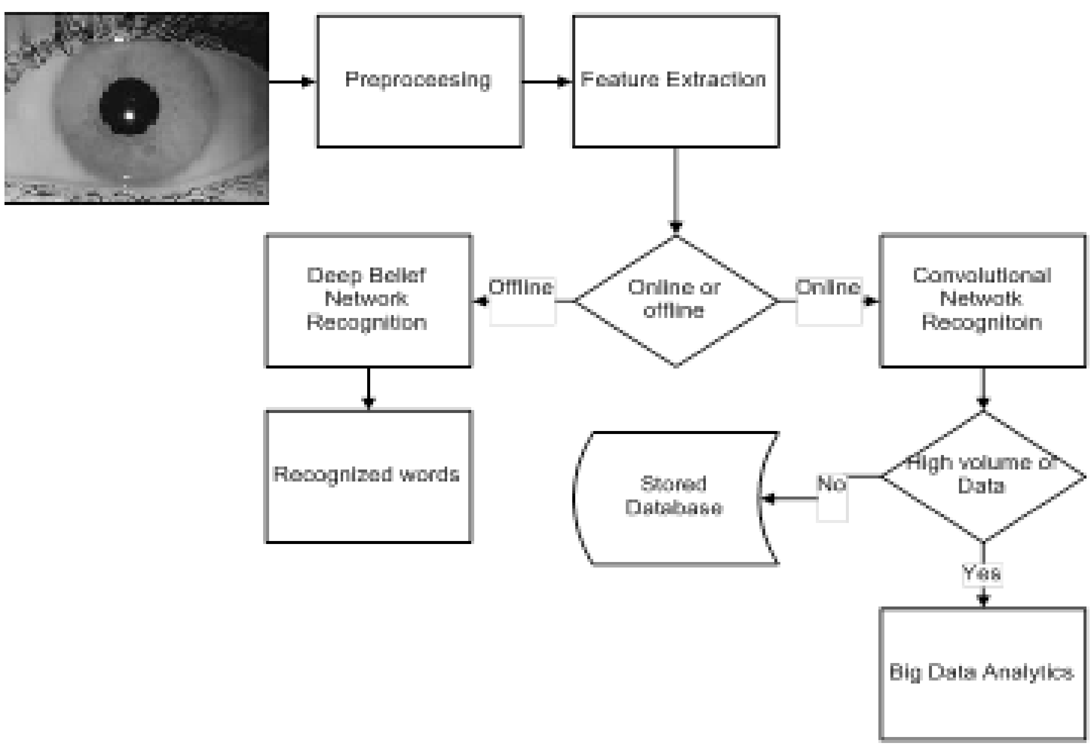

Figure 0: Feature Extraction-Deep Learning

In the Banking side of the system, the bank manager has to use his finger print and iris image to open the system at the same to edit and modify the database only the privileged user can access it.

Iris Manager: It is responsible for maintaining the privilege users and controls the access to the iris server.

Iris Monitor: it is responsible to maintain the iris in the db servers in proper way such that millions of iris of the users are monitored and reported immediately when needed.

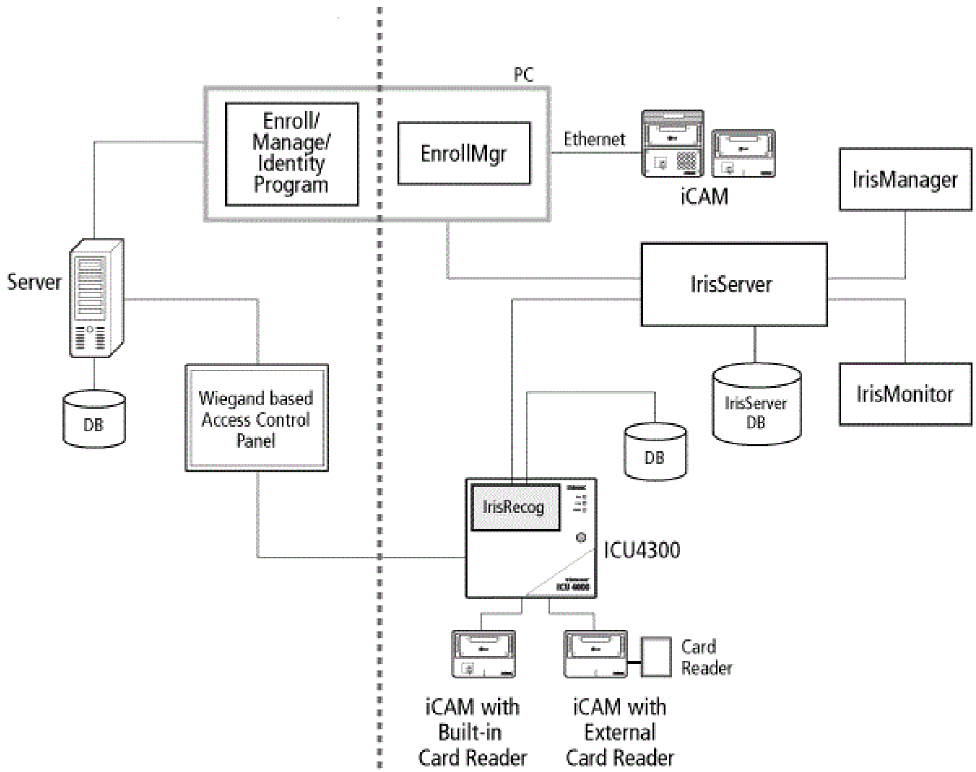

Figure 1: System architecture of the smart ATM (preprocessing and Feature extraction)

Iris Server keeps itself accessible to the iris server db when a request is raised immediate response must be made with reference to the iris db.

iCAM here is referred to the device that is used to scan the user iris. generally, iris scanner is used to read and send the captured image to the system.

6. ALGORITHM DETAILS

The first step of implementing the is algorithm is by applying houghs circle detection algorithm for identifying the eye portion and then implementing the canny edge detection algorithm for identifying the iris portion. By this way we make sure less fake matched occurs [23-26].

A. Hough's algorithm

The linear Hough transform algorithm uses a two-dimensional array, called an accumulator, to detect the existence of a lines and curves described by.

$$R = x \cos \theta + y \sin \theta$$

The dimension of the accumulator equals to the total number of unknown parameters which is considering quantized values of r and θ as pair of (r, θ). At position (x, y) where x and y are the pixel for each pixel its neighbourhood, the Hough transform algorithm figures out if there are enough evidences of lines to the pixel. Provided that this is true, it will ascertain the parameters (r, θ) of that line, and afterward search for the accumulators bin whether the parameters fall into it, and augmentation the estimation of bin to move further. By finding the bins with the most astounding values, that is by taking at local maxima in the accumulator values, the in all likelihood lines can be extracated with their (approximate) geometric positions.

Circle Detection Process

The Circular Shapes identification process in Hough Space is relatively simple process as follows,

- An accumulator space made up of a cell of each pixel of the image as initially created.
- For each cell initialize the values to 0.
- For each (i, j) cell pixel in the image, All the cells are incremented according to the circle equation as follows:

$$(r^2 = (i - a)^2 + (j - b)^2)$$

- Which may be the center of the circle and these cells are represented by letter '*a*' in equation.
- So all possible values of b are evaluated which satisfy the equation to find the (a, b) pair for all value found in the previous process.
- Hunt down the nearby maxima cells, these are the cell which has a worth, more prominent than each other cell in its neighborhood. These cells are the one with the most noteworthy likelihood of being the area of the iris circle which we are attempting to find.

Note: In many issues, we will know the radius of the circle we are attempting to find in advance, be that as it may on the off chance that this is not the case then we can utilize a three-dimensional accumulator space, this is a great deal all the more computationally tedious and costly. This strategy can likewise identify circles that are mostly outside of the accumulator space if enough of its range is still present inside it.

B. Canny Edge Detection Algorithm

The algorithm used to extract the iris portion from the scanned image which is processed by the hough's algorithm is given to Canny's Edge Detection Algorithm. This algorithm is also known as optimal edge detector to professionals.

- The first step is to find and filter out any noise in the original image before trying to locate and detect any edges. The Gaussian spatial filter can be computed using a simple mask. After calculating a suitable mask, the Gaussian smoothing can be performed using standard convolution methods.
- Gaussian filter is simply used to reduce noise in the image and make it more feasible to process in next step.
- The larger the width of the Gaussian mask, the lower is the detector's sensitivity to noise. The localization error in the detected edges also increases slightly as the Gaussian width is increased.
- The following shows the sample Gaussian mask which smooths the image by 2D convolutions, by calculating the separate x and y values we can use the center pixel to simply calculate but it is not appropriate to do so because the value of the Gaussian varies non-linearly across the pixel.

$$\frac{1}{115}\begin{array}{|c|c|c|c|c|}\hline 2 & 4 & 5 & 4 & 2 \\ \hline 4 & 9 & 12 & 9 & 4 \\ \hline 5 & 12 & 15 & 12 & 5 \\ \hline 4 & 9 & 12 & 9 & 4 \\ \hline 2 & 4 & 5 & 4 & 2 \\ \hline \end{array}$$

Discrete approximation to Gaussian function with ô = 1.0

I. After smoothing the image and eliminating the noise, the next step is to find the strength of edge using sobel operator. The Sobel operator uses a pair of 3x3 convolution masks along x-direction (columns) and y-direction (rows). They are shown below:

–2	0	+1
–2	0	+2
–1	0	+1

G_x

+1	+2	+1
0	0	0
–1	–2	–1

G_y

- The magnitude, or edge strength, of the gradient is then approximated using the formula:

$$|G| = |G_x| + |G_y|$$

- The direction is found using the formula,

$$\Theta = \tan^{-1} (G_y/G_x)$$

II. Also, when the gradient in x direction is zero, the edge direction has to be to 90° or 0°. If G_y value is zero, the edge direction will be 0°. Otherwise the edge direction will equal 90°.

- After calculating the edge direction, the next step is to relate them with the image,

```
xy xy xy xy xy
xy xy xy xy xy
xy xy p  xy xy
xy xy xy xy xy
xy xy xy xy xy
```

- By looking at pixel "**p**", there are four possible directions **0°** (in the horizontal direction), **45°** (along the positive diagonal), **90°** (in the vertical direction), or **135°** (along the negative diagonal).
- Any edge direction falling within the **yellow range** (0° to 22.5° & 157.5° to 180°) is set to 0°, **green range** (22.5° to 67.5°) is set to 45°, **blue range** (67.5° to 112.5°) is set to 90°, **red range** (112.5° to 157.5°) is set to 135°.
- The edge orientation has to be resolved into one of these four directions as shown above.
- After the edge directions are known, non-maximum suppression has to be applied to trace along the edge in the edge direction to give a thin line in the output image.

- Finally, Hysteresis is used as a means of eliminating streaking which is breaking up of an edge contour caused by the operator output fluctuating above and below the threshold.

7. WORKING MODULE

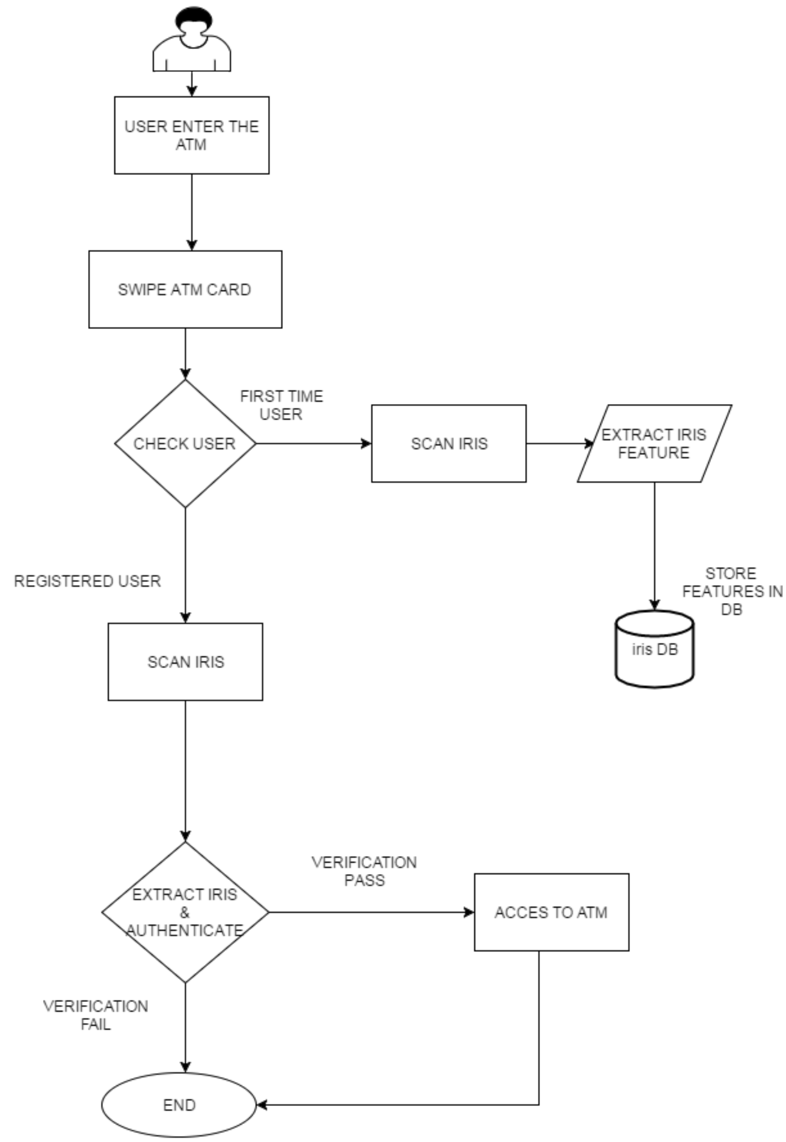

Figure 2: Working model of ATM

8. IRIS EXTRACTION

Initially the image of the human eye is scanned through the iris scanner and the output which is given by the device is a image, which is of format Jpeg. Later the image is loaded in to the memory. Then hough's transformation is performed to detect the iris portion which is extracted as K7 image template. Later the image is further processed through the canny edge detection algorithm to detect the identical features that are unique for each and every human being.

The following flow chart describes the iris extraction.

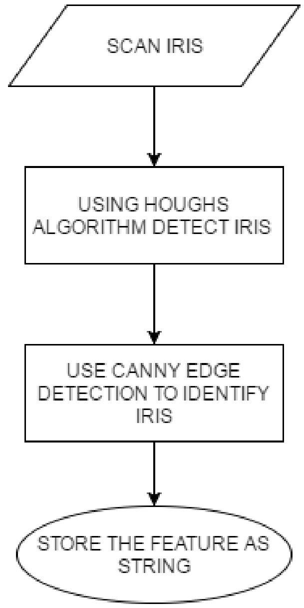

Figure 3: Feature extraction

1. Recognition using Deep Learning

Deep learning is demonstrated as an collection of machine learning strategies that take in various levels of representations in Deep architecture design. Deep Belief Networks (DBN) and Convolutional neural networks (CNN) are two well-established deep architectures and brief explanations about these two architectures are discussed in this section.

Feature extraction is the procedure of separating data from the preprocessed information which is utilized for data classification purpose. The Characters from the preprocessing stage are given as inputs to the feature extraction stage. The frames that contain the standardized characters are separated into a few non-overlapping zones. Then for each zone the pixel density is calculated and those pixel densities are used as a feature. Each zone has different sizes and these zones were utilized in the work ranging from 292 to 898 pixels. There will be 256 different zones and 256 features if the zone size is 292. In same case if the zone size is 492 then there will be 64 different zones and 64 features. When the zone size is 888 then there will be 16 different zones and 16 features. By using these extracted features the training set and test set are generated.

2. Deep Belief Networks

Conventional Neural Networks prompts continuous poor performance in light of the fact that the network systems are proned to get trapped in nearby optima of a non-convex objective function [14]. Also, the unlabeled data are not taken into profound consideration, which are frequently bottomless and cheap to gather in Big Data. These issues are lightened utilizing a Deep Belief Network (DBN) which utilizes a deep architecture that is fit for learning feature representations from both the marked and unlabeled data exhibited to it [21]. This Deep belief Network fuses both both supervised fine-tuning strategies and unsupervised pre-training to build the general powerful model. The unsupervised stages mean to learn data distributions without utilizing any label data and supervised stages perform neighborhood scan for calibrating.

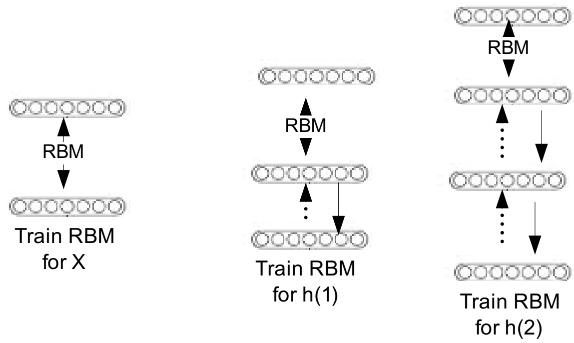

Figure 4: Typical DBN architecture composed of a stack of RBM's

Figure 4 demonstrates an average DBN architecture, which is made out of a stack of Restricted Boltzmann Machines (RBMs) and separation errands as one or increasingly extra layers. RBMs are probabilistic generative models that take in a joint probability distribution of observed (training) data without using data labels. They can successfully use a lot of unlabeled data for misusing complex information structures. Once the structure of a DBN is resolved, the objective for learning is to take in the weights (and biases) between layers. This is led firstly by an unsupervised learning of RBMs. In a typical RBM there are two layers in which the nodes in one layer are completely associated with other layer nodes however there is no association for the nodes in same layer. Along these lines, every node is autonomous of different nodes in the same layer however subsequently rely on upon all nodes in the other layer. This trademark permits us to prepare the generative weights W of each RBMs.

3. Training a Deep Neural Network

(a) Initially using the inputs that are directly received from the pixels are used to train a layer of features.

(b) The activations of those perfectly trained features are treated as they were pixels and in second hidden layer they learn the features of features.

(c) In order to improvise the vibrational lower bound on the log probability of the training data an another layer of features is added to neurons each time and it has been proved to be successful.

Before adjusting, a layer-by-layer pre-preparing of RBMs is performed. The yields of a RBM are nourished as inputs to the following RBM and the procedure rehashes until all the RBMs are pre prepared. This layer-by-layer unsupervised learning is critical in DBN training as basically it maintains a strategic distance from nearby optima and mitigates the over-fitting issue that is observed when a large number of parameters are utilized. Besides, the calculation is exceptionally effective as far as its time multifaceted nature, which is direct to the number and size of RBMs [10]. Highlights at various layers contain diverse data about information structures with more elevated amount highlights developed from lower-level components. Note that the quantity of stacked RBMs is a parameter predetermined by users and pre-preparing requires just unlabeled data (for good speculation).

For a simple RBM the sampling probabilities of both the visible and hidden layers are calculated using Bernoulli distribution as follows [10]:

$$\mathrm{P}(h_j = 1 \mid v; \mathrm{W}) = \sigma\left(\sum_{i=1}^{j} w_{ij} v_j + a_i\right) \tag{1}$$

$$P(h_j = 1 \mid h; W) = \sigma\left(\sum_{i=1}^{j} w_{ij} h_j + b_i\right) \tag{2}$$

where, v and h speaks to an $I \times 1$ visible unit vector and a $J \times 1$ hidden unit vector, individually; W is the lattice of weights (w_{ij}) associating the visible and hidden layers; a_j and b_i are predisposition (bias) terms; and σ (■) is a sigmoid capacity. For the instance of real-valued visible units, the conditional probability distributions are somewhat distinctive: regularly, a Gaussian-Bernoulli conveyance is expected and $p(v_i \mid h; W)$ is Gaussian [18].

There are different varieties for pre-training: rather than utilizing RBMs, for instance, stacked de-noising auto-encoders and stacked predictive sparse coding are likewise proposed for unsupervised feature learning. At the point when an extensive number of training data is accessible it has been demonstrated that, a fully supervised training using random initial weights rather than the pre-trained weights (i.e., without utilizing RBMs or auto-encoders) will for all intents and purposes function admirably. For instance, a discriminative model begins with a system with one single hidden layer (i.e., a shallow neural network), which is trained by back propagation strategy.

4. Convolutional Neural Networks

A Convolutional Neural Network is made out of numerous layers of progressive system with some layers for feature representations (or feature maps) and others as a sort of ordinary neural systems for characterization [5]. It frequently begins with two changing sorts of layers called convolutional and sub sampling layers: convolutional layers perform convolution operations with a few channel maps of equivalent size, while sub testing layers diminish the sizes of continuing layers by averaging pixels inside a little neighborhood (or by max-pooling [5], [7]).

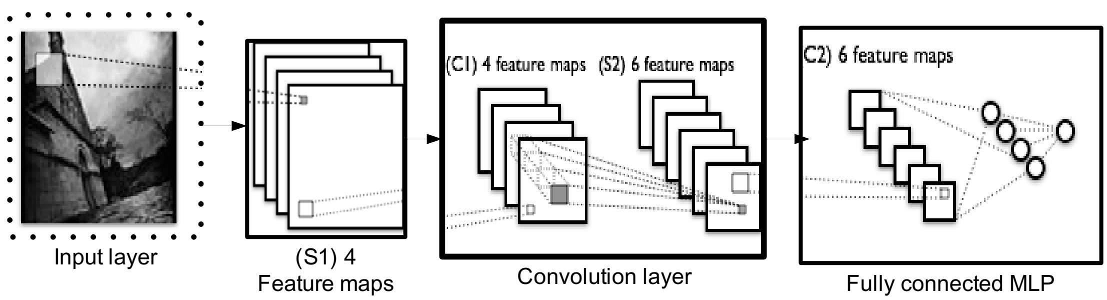

Figure 5: Typical CNN architecture composed of layers for feature representations (or feature maps)

Figure 5 demonstrates a typical architecture of CNNs. The input is initially convoluted with an arrangement of filters (C layers in Figure 5). These 2D filtered data are called feature maps. After a nonlinear transformation, a sub sampling is further performed to diminish the dimensionality (S layers in Figure 5). The grouping of convolution/sub sampling can be rehashed ordinarily (predetermined by clients).

As outlined in Figure 5, the most reduced level of this architecture is the input layer with 2D $N \times N$ pictures as our inputs. This convolution layers are made out of numerous feature maps, which are built by convolving inputs with various channels intend to be as weight vectors.

The sub-examining layer lessens the spatial determination of the feature map. Every unit in the sub-sampling layer is developed by averaging a 2×2 area in the feature map or by max pooling over a little locale.

5. Deep Learning for Massive Amounts of Data

While Deep learning has demonstrated noteworthy results in numerous applications, its training is not a trifling task for Big Data learning because of the way that iterative calculations inherit in most deep learning calculations are frequently greatly hard to be parallelized. In this manner, with the phenomenal development of business and scholarly information sets as of late, there is a surge in enthusiasm for viable and scalable parallel algorithms for training deep models. Rather than shallow designs where couples of parameters are desirable over maintain a strategic distance from over fitting issues, deep learning algorithms make the most of their prosperity with countless neurons, regularly bringing about a large number of free parameters. Consequently, substantial scale deep learning frequently includes both expansive volumes of data's and extensive models. These deep learning structures are especially suited for hugely parallel processing with more transistors committed for data proceeding requirements. These recently grew profound learning systems have indicated noteworthy advances in making substantial scale deep learning practical.

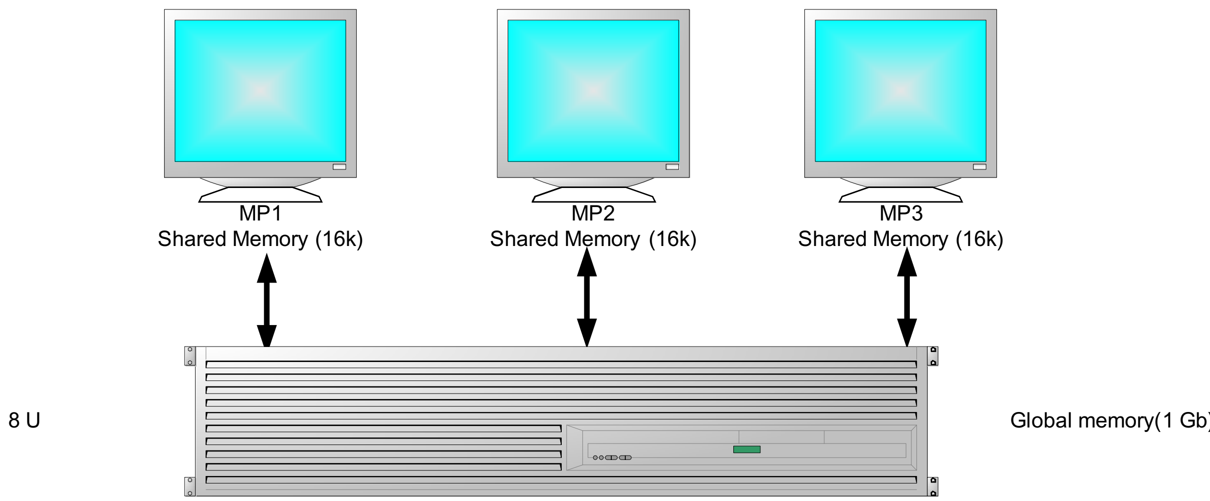

Figure 6: Typical CUDA-capable GPU with three multi-processors

Figure 6 demonstrates a schematic for a normal CUDA-fit GPU with four multi-processors. Each multi-processor (MP) comprises of a few streaming multiprocessors (SMs) to shape a building block (Figure 6 indicates two SMs for every square). Every SM has various stream processors (SPs) that share control rationale and low-latency memory. Besides, each GPU has a worldwide memory with high transfer speed and high inactivity when gotten to by the CPU (host). This design takes into consideration two levels of parallelism: direction (memory) level (i.e., MPs) and string level (SPs). This SIMT (Single Instruction, Multiple Threads) architecture takes into account thousands or a huge number of strings to be run simultaneously, which is most appropriate for operations with huge number of math operations and little get to times to memory. Such levels of parallelism can likewise be adequately used with uncommon consideration on the information stream when creating GPU parallel computing applications.

5. Deep Learning for High Velocity of Data

Developing difficulties for Big Data learning likewise emerged from high velocity: information are creating at greatly fast and should be handled in an opportune way. One answer for learning from such high speed information is internet learning approaches. Web learning learns one occasion at once and the genuine name of every example will soon be accessible, which can be utilized for refining the model [15] [16]. This consecutive learning technique especially works for Big Data as present machines can't hold the whole dataset in memory.

9. SCREENSHORTS

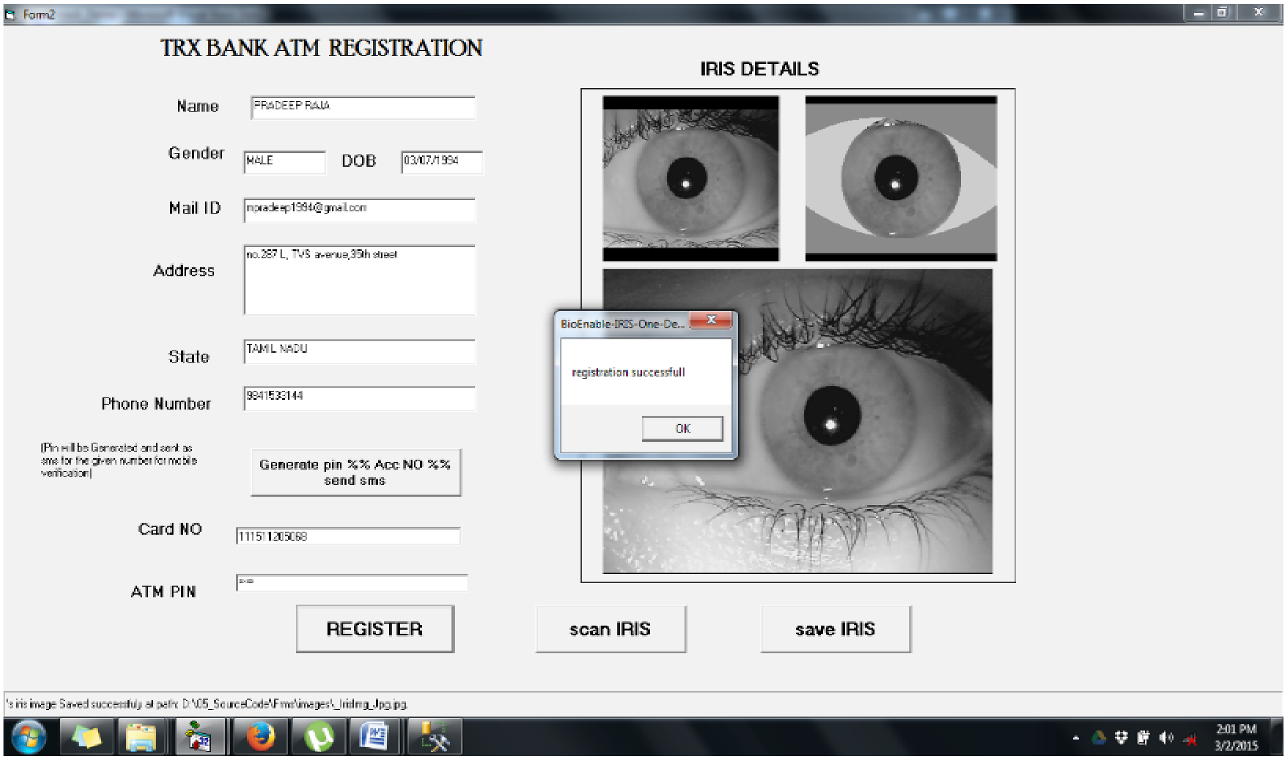

Figure 4: Registering user and Iris capture

Figure 5: User Login in ATM

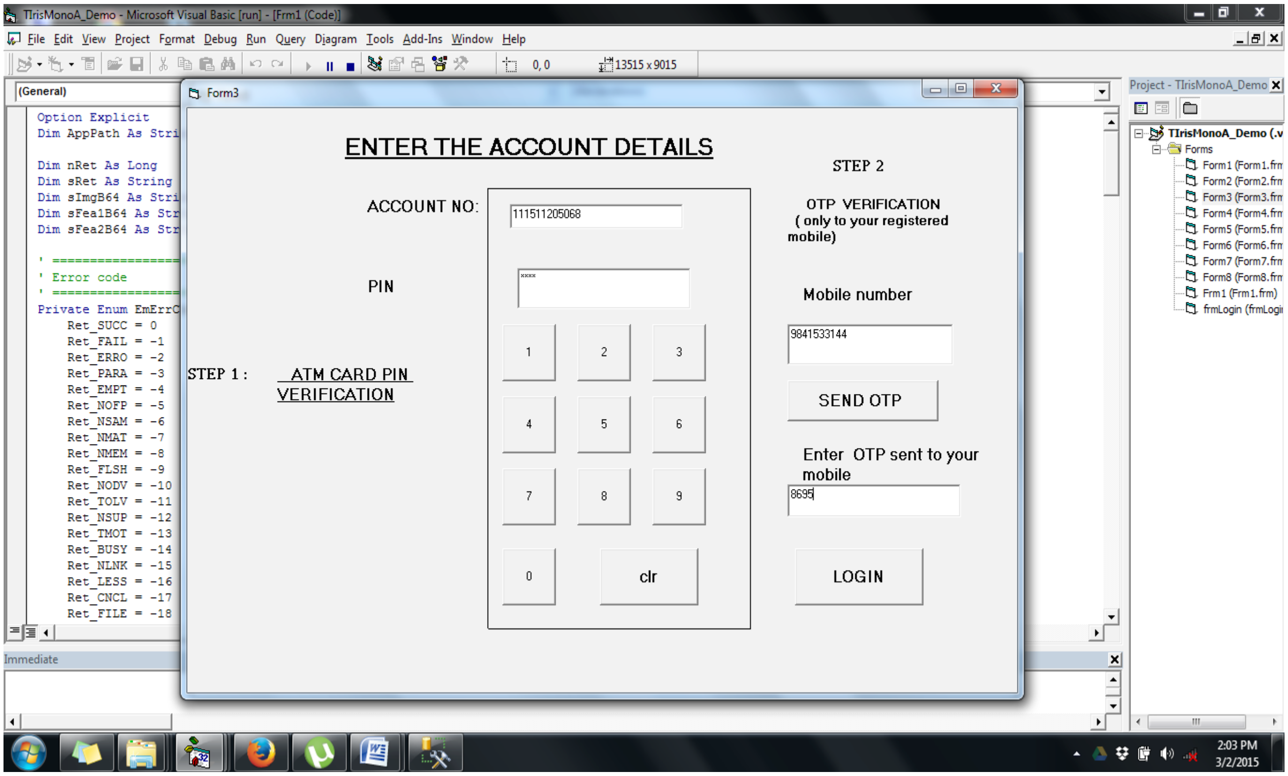

Figure 6: Level of verification

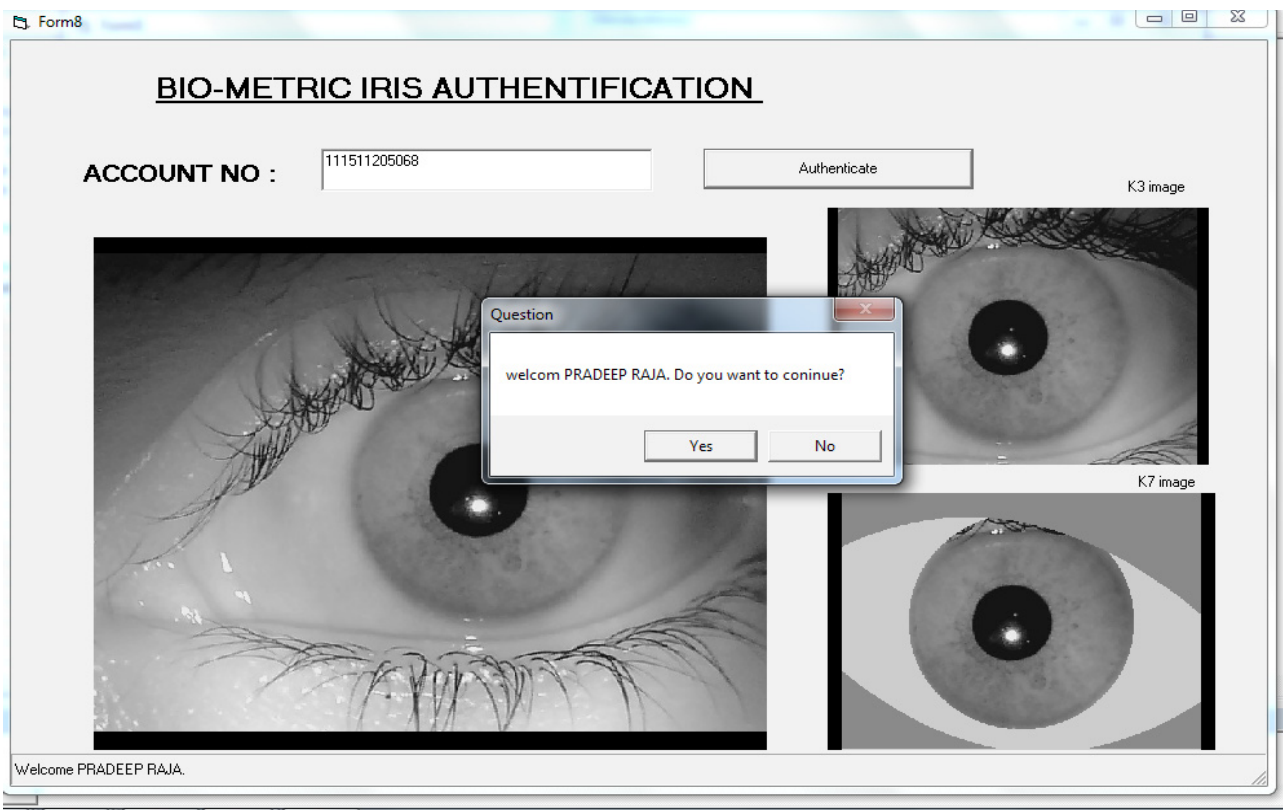

Figure 7: Iris extraction and comparing

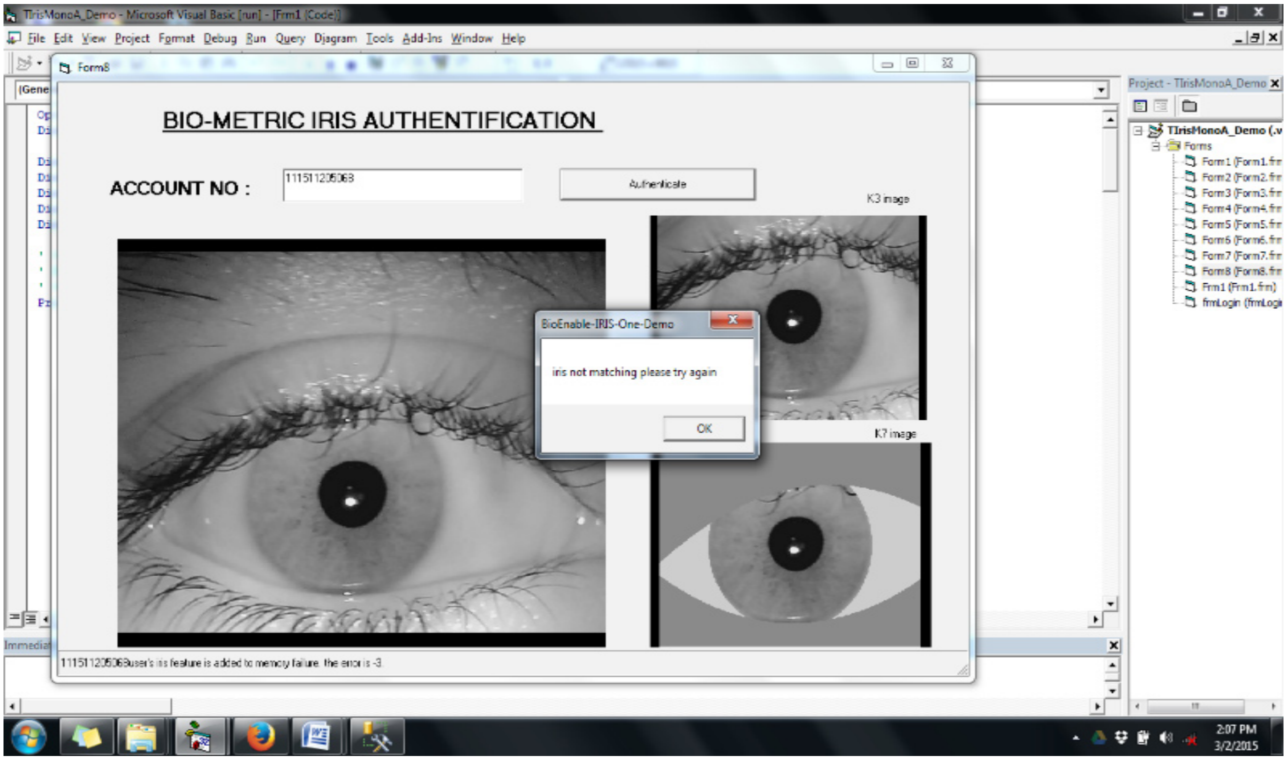

Figure 8: Failed Iris comparison with random eye

10. CONCLUSION

There is a huge growth of market and can be in great demands all over the world. As this "**Biometric Based Authentication In ATM**" provides high security and more authentications to the existing system, against illegal use of debit card, it also provides an easy way to catch the criminals. This project has a scope to become popular and highly demanded technology like deep learning because each and every person will be having unique iris pattern which is not possible to easily identify or forge and though the process is little time consuming it can be completely made feasible through the deep learning mechanism and it provides a best security at ATM's.

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