EYE BLINK FOR USER AUTHENTICATION

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Abstract – *Personal identification numbers are widely used for user authentication and security. Password verification using PINs requires users to enter a physical PIN, which can be vulnerable to password breakage or hacking. via shoulder surfing or thermal tracking. PIN authentication with hands-off eye blinks PIN entry techniques, on the other hand, leaves no physical footprints behind and therefore offSers a more secure password entry option. Eye blinks-based authentication refers to finding the eye blinks across sequential image frames, and generating the PIN. This project presents a real-time application we combine eye blink-based PIN entry, and face detection and OTP to avoid shoulder surfing and thermal tracking attacks.*

1.INTRODUCTION

One of the security requirements for general terminal authentication systems is to be easy, fast and secure as people face authentication mechanisms every day and must authenticate themselves using conventional knowledge-based approaches like passwords. But these techniques are not safe because they are viewed by malicious observers who use surveillance techniques such as shoulder surfing to capture user authentication data. Also, there are security problems due to poor interactions between systems and users. Eye blinking is a natural interaction method and security systems based on eye blink tracking provide a promising solution to the system security and usability. The aim of this paper is to review techniques or solutions to dealing with eye blink in security systems.

1.1 MOTIVATION

The use of personal identification numbers (PINs) is a common user authentication method for 2 many applications, such as money management in automatic teller machines (ATMs), approving electronic transactions, unlocking personal devices, and opening doors. Authentication is always a challenge even when using PIN authentication, such as in financial systems and gateway management. According to European ATM Security, fraud attacks on ATMs increased by 26% in 2016 compared to that of 2015. The fact that an authorized user must enter the code in open or public places make PIN entry vulnerable to password attacks, such as shoulder surfing as well as thermal tracking, so we have motivated to implement the real time eye blink based password authentication system to avoid the shoulder surfing and thermal tracking attacks.

2. SYSTEM ANALYSIS

2.1 EXISTING SYSTEM

The user's PIN is still the token of authentication, and the security is improved when the input method is changed. Rather than inserting numbers, an eye movement is performed by the user representing theassociated digits. Eye-Pass Shapes can be considered simpler to be detected than the exact location of the user's look and can work with cheap devices.

2.2 PROPOSED SYSTEM

The main principle of the proposed system is to generate eye blink-based PIN generation system that is dependent on computerized vision technology. It is achieved using different methodologies such as face and eye detection, eye blink detection, rectangular and circular pupil edge detection and eye tracking.

2.3 SCOPE

The use of personal identification numbers (PINs) is a common user authentication method for many applications, such as money management in automatic teller machines (ATMs), approving electronic transactions, unlocking personal devices, and opening doors. Flawless identity authentication remains a challenge even when PIN authentication is used, such as in financial systems and gate access control. According to European ATM Security, fraud attacks on ATMs increased by 26% in 2016 compared to that of 2015. The fact that an authorized user must enter the code in open or public places make PIN entry vulnerable to password attacks, such as shoulder surfing as well as thermal tracking.

3. SYSTEM DESIGN

3.1 System Architecture

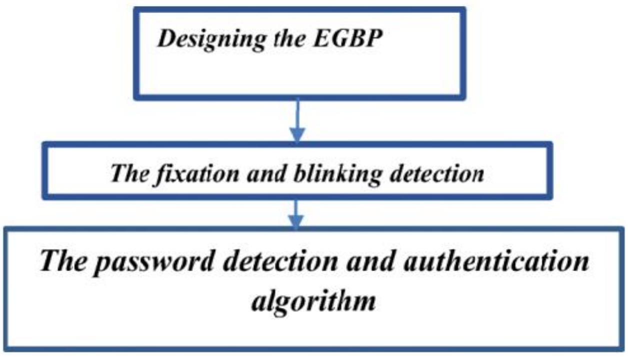

Fig 3.1 Architecture outline of the classification of eye-blink

The above figure depicts the evaluation of the experiment by step-by-step stages. In the first step, the real time dataset is loaded and the data becomes ready for pre-processing. We are recognizing the face using LBPH and capture the eye blinks using HAAR cascade eye detection, Authenticating user id and PIN

3.2 Flow Chart

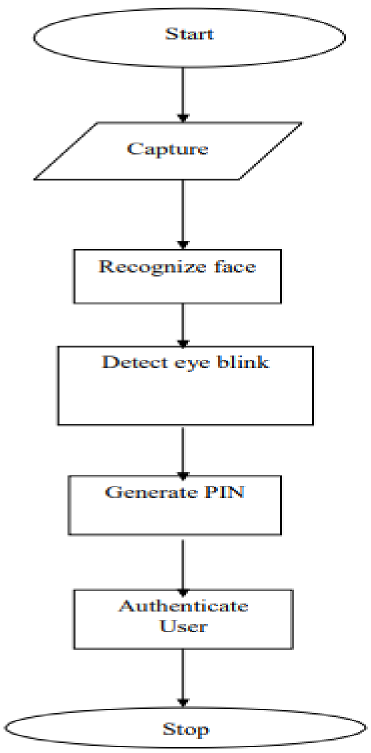

Fig 3.2 Flow Chart

3.3 Use Case Diagram

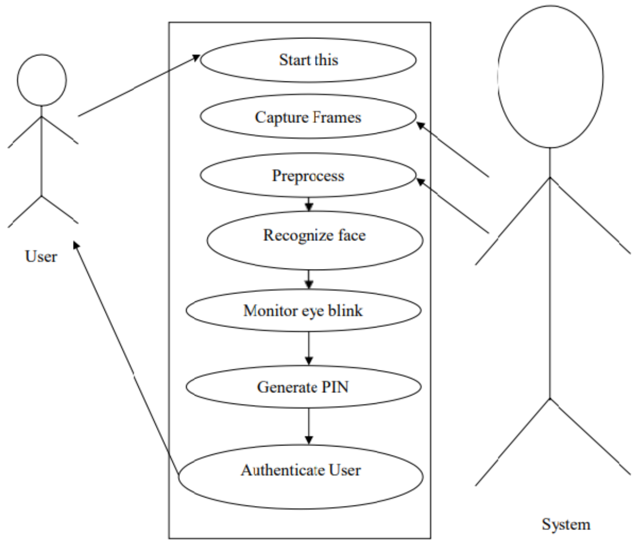

Fig 3.3 Use Case Diagram

3.4 Sequence Diagram

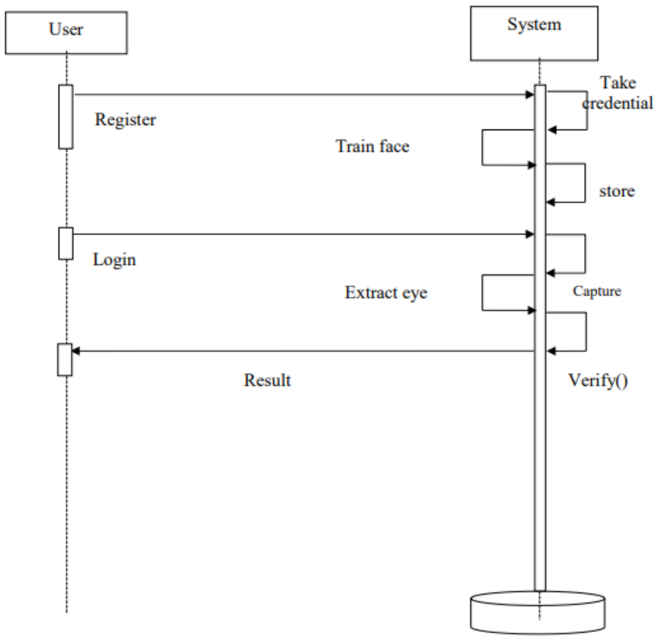

Fig 3.4 Sequence Diagram

3.5 Data Flow Diagram

Level 0:

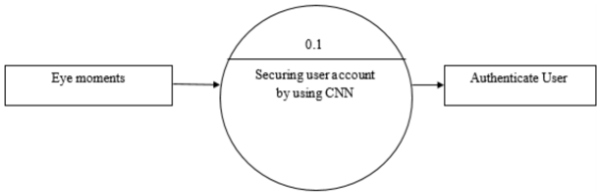

Fig 3.5.1 Level 0 Data Flow Diagram

Level: 0 describes the overall process of the project. We are using users eye moments as input. System will use the conventional neural network to secure user account information from shoulder surfing attacks.

Level 1:

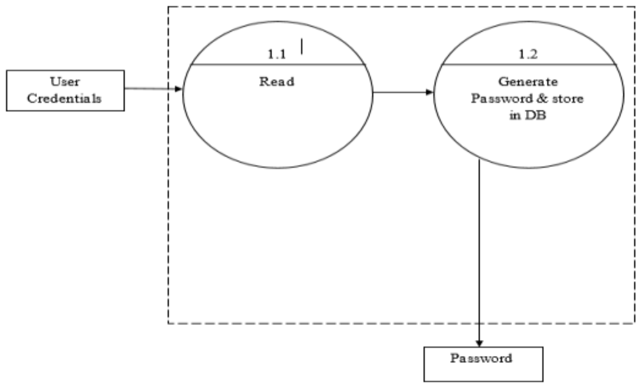

Fig 3.5.2 Level 1 Data Flow Diagram

Level 2:

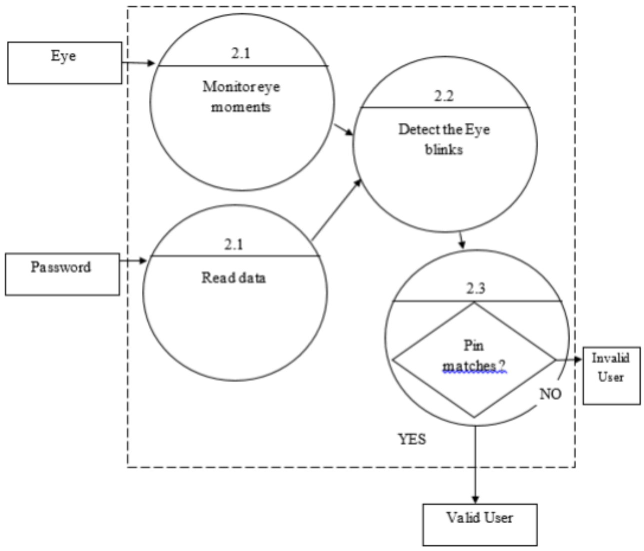

Fig 3.5.3 Level 2 Data Flow Diagram

3.6 Class diagram

Class diagram is a static diagram. It represents the static view of an application. Class diagram is not only used for visualizing, describing, and documenting different aspects of a system but also for constructing executable code of the software application. Class diagram describes the attributes and operations of a class and also the constraints imposed on the system. The class diagrams are widely used in the modelling of object-oriented system because they are the only UML diagrams, which can be mapped directly with object-oriented languages. Class diagram shows a collection of classes, interfaces, associations, collaborations, and constraints. It is also known as a structural diagram

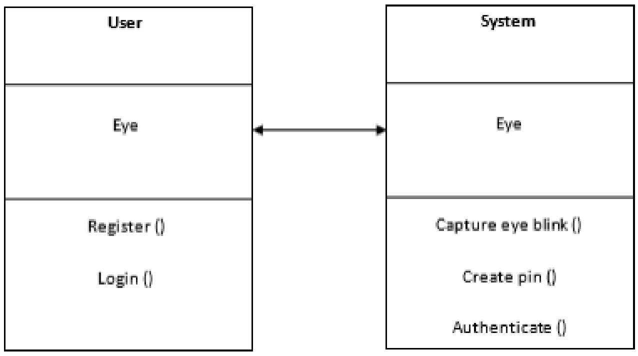

Fig 3.6 Class Diagram

3.7 Activity diagram

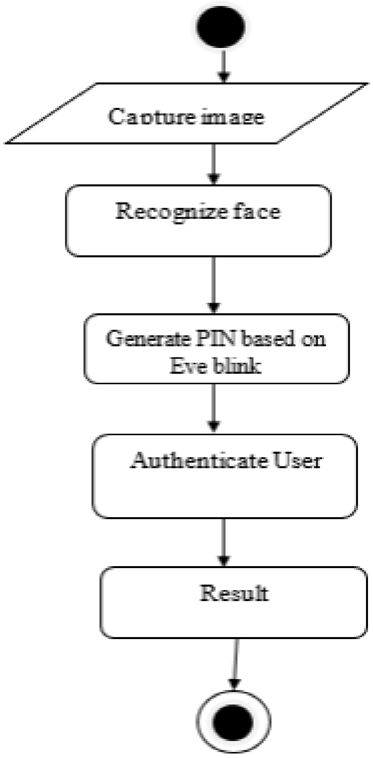

Fig 3.7 Activity Diagram

4. ALGORITHM APPLIED

4.1 HAAR CASCADE CLASSIFIER

Haar Cascade is a machine learning object detection algorithm used to identify objects in an image or video and based on the concept of features proposed by Paul Viola and Michael Jones in their paper "Rapid Object Detection using a Boosted Cascade of Simple Features" in 2001. It is a machine learning based approach where a cascade function is trained from a lot of positive and negative images. It is then used to detect objects in other images.

The algorithm has four stages:

1. Haar Feature Selection
2. Creating Integral Images
3. Adaboost Training
4. Cascading Classifiers

4.1.1 Cascade classifier

The cascade classifier consists of a collection of stages, where each stage is an ensemble of weak learners. The weak learners are simple classifiers called decision stumps. Each stage is trained using a technique called boosting. Boosting provides the ability to train a highly accurate classifier by taking a weighted average of the decisions made by the weak learners. Each stage of the classifier labels the region defined by the current location of the sliding window as either positive or negative. Positive indicates that an object was found and negative indicates no objects were found. If the label is negative, the classification of this region is complete, and the detector slides the window to the next location. If the label is positive, the classifier passes the region to the next stage. The detector reports an object found at the current window location when the final stage classifies the region as positive.

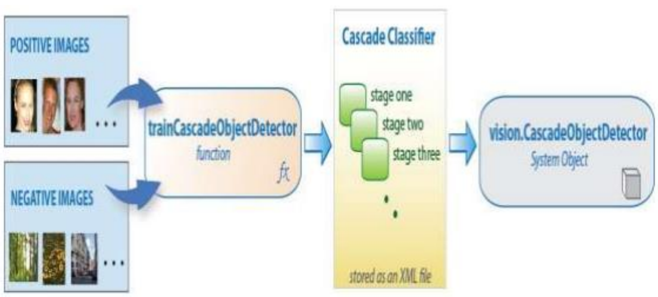

Fig 4.1.1 Cascade Classifier

The stages are designed to reject negative samples as fast as possible. The assumption is that the vast majority of windows do not contain the object of interest. Conversely, true positives are rare and worth taking the time to verify.

- A true positive occurs when a positive sample is correctly classified.
- A false positive occurs when a negative sample is mistakenly classified as positive.
- A false negative occurs when a positive sample is mistakenly classified as negative.

4.2 LBPH Face Reorganization

Local Binary Patterns Histogram algorithm was proposed in 2006. It is based on local binary operator. It is widely used in facial recognition due to its computational simplicity and discriminative power. The steps involved to achieve this are:

- creating dataset
- face acquisition
- feature extraction
- classification

The LBPH algorithm is a part of OpenCV.

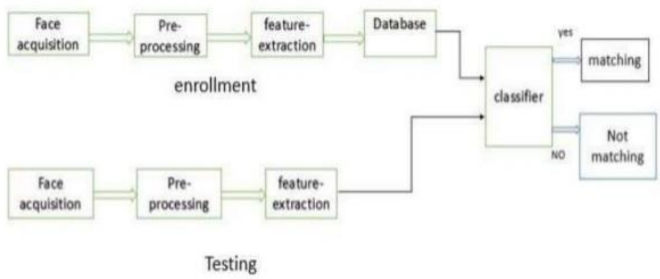

Fig 4.2 Creating Dataset

5. IMPLEMENTATION

5.1 Capturing of Face

Proposed System consists of a camera, placed in the classroom to capture all the students. From these captured image frames, using the OpenCV and system will detect the student's face in the captured image using Haar cascade face detection technique.

5.2 Training phase

In the training phase we are applying the LBPH (local binary pattern Histogram) algorithm.

5.3 Face recognition

We proposed face detection technique by incorporating Haar cascade classifier and LBPH techniques. This technique does not play out any sub-sampling, but it optimizes over all sub windows.

Fig 5.3 Face Recognition

5.4 Tracking of the eyes

We track the eye by looking for the darkest pixel in the predicted region. In order to recover from tracking errors, we make sure that none of the geometrical constraints are violated. If they are, we re-localize the eyes in the next frame. To find the best match for the eye template, we initially center it at the darkest pixel, and then perform a gradient descent in order to find a local minimum.

5.5 Authentication of User

We are collecting the generated PIN and checking with the system databases if user id and PIN matches, System will send OTP to the user's mobile number if user enters the correct OTP system will authenticate the user.

6. RESULT

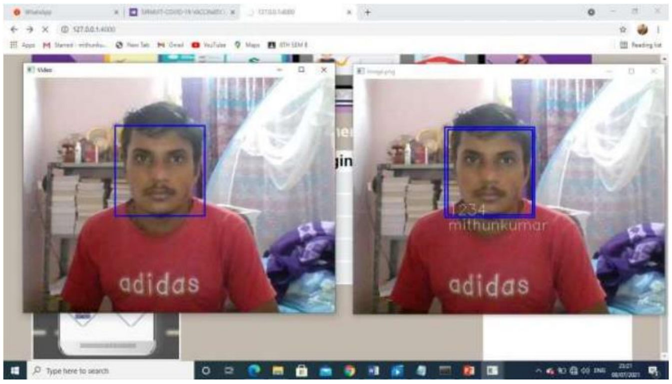

Fig 6.1(a) User Face Authentication

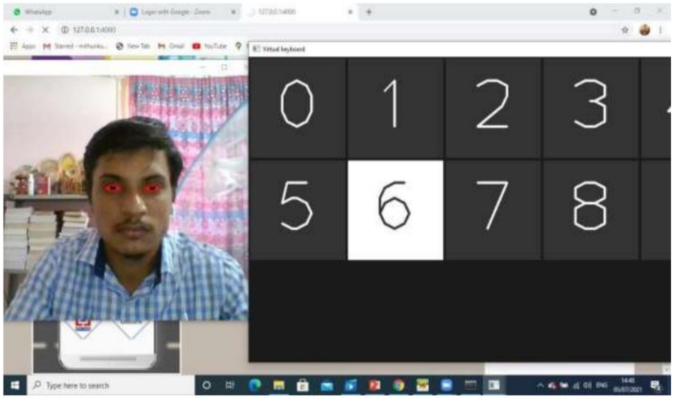

Fig 6.1(b) Eye Blink Authentication

7. CONCLUSIONS

Smart-camera based eye_tracking system has been incorporated into a new application for gaze based PIN identification. The system has been successfully tested with a nine-digit keypad, and can be extended to character and digit combination password entry. Stray data points in the scatter plots are generally associated with transitional movement of the eyes between digits. In addition, screen size affects the precision within the clusters, and must be calibrated for each screen and keypad

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