International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 04 | April - 2023 Impact Factor: 8.176 ISSN: 2582-3930

MULTILEVEL AUTHENTICATION SYSTEM BASED ON PERIOCUALR FEATURES USING DEEP LEARNING ALGORITHM

Ajantha S,Nithya C,Varshini K

ABSTRACT

The use of biometric for identification purposes requires that a particular biometric factor be unique for each individual that it can be calculated, and that it is invariant over time. Biometrics such as signatures, photographs, fingerprints, voiceprints and retinal blood vessel patterns all have noteworthy drawbacks. Although signatures and photographs are cheap and easy to obtain and store, they are impossible to identify automatically with assurance, and are easily forged. Human iris on the other hand as an internal organ of the eye and as well protected from the external environment, yet it is easily visible from within one meter of distance makes it a perfect biometric for an identification system with the ease of speed, reliability and automation. Iris recognition is regarded as the most reliable and accurate biometric identification system available. Iris recognition is an automated method of biometric identification that uses mathematical pattern-recognition techniques on images of the irises of an individual's eyes, whose complex random patterns are unique. In this work it is proposed to implement a face and iris recognition system, where Grassmann algorithm, Curvelet transform and deep neural network is used to segment the face, eye and iris region. A template of the detected region is created using template matching for recognition is based on features in real time enrolment system. The results shows that the proposed method is efficient for existing iris image based biometric recognition.

KEYWORDS: Authentication system, Biometric system, Face recognition, Peri-ocular features, Deep learning algorithm

1. INTRODUCTION

Biometrics refers to metrics related to human characteristics. Biometrics authentication (or realistic authentication) is used in computer science as a form of identification and access control. It is also used to identify individuals in groups that are under surveillance. Biometric identifiers are then distinctive, measurable characteristics used to label and describe individuals. Biometric identifiers are often categorized as physiological versus behavioral characteristics. Physiological characteristics are related to the shape of the body. Examples include, but are not limited to fingerprint, palm veins, face recognition, DNA, palm print, hand geometry, iris recognition, retina and odour/scent. Behavioural characteristics are related to the pattern of behaviour of a person, including but not limited to typing rhythm, gait, and voice. Some researchers have coined the term behaviour-metrics to describe the latter class of biometrics.

More traditional means of access control include token-based identification systems, such as a driver's license or passport, and knowledge-based identification systems, such as a password or personal identification number. Since biometric identifiers are unique to individuals, they are more reliable in verifying identity than token and knowledge-based methods; however, the collection of biometric identifiers raises privacy concerns about the ultimate use of this information. Multimodal biometric systems use multiple sensors or biometrics to overcome the limitations of unimodal biometric systems. For instance iris recognition systems can be compromised by aging irises and finger scanning systems by worn-out or cut fingerprints. While unimodal biometric systems are limited by the integrity of their identifier, it is unlikely that several unimodal systems will suffer from identical limitations. Multimodal biometric systems can obtain sets of information from the same marker (i.e., multiple images of an iris, or scans of the same finger) or information from different biometrics (requiring fingerprint scans and, using voice recognition, a spoken pass-code).

Functionality:

Many different aspects of human physiology, chemistry or behavior can be used for biometric authentication. The selection of a particular biometric for use in a specific application involves a weighting of several factors. And identified seven such factors to be used when assessing the suitability of any trait for use in biometric authentication.

- Universality means that every person using a system should possess the trait.
- Uniqueness means the trait should be sufficiently different for individuals in the relevant population such that they can be distinguished from one another.
- Permanence relates to the manner in which a trait varies over time. More specifically, a trait with 'good' permanence will be reasonably invariant over time with respect to the specific matching algorithm.
- Measurability (collectability) relates to the ease of acquisition or measurement of the trait. In addition, acquired data should be in a form that permits subsequent processing and extraction of the relevant feature sets.
- Performance relates to the accuracy, speed, and robustness of technology used (see performance section for more details).
- Acceptability relates to how well individuals in the relevant population accept the technology such that they are willing to have their biometric trait captured and assessed.

Proper biometric use is very application dependent. Certain biometrics will be better than others based on the required levels of convenience and security. No single biometric will meet all the requirements of every possible application.

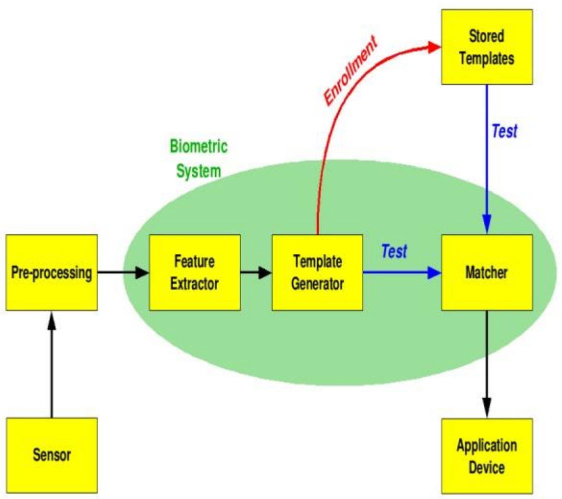

Fig 1 Biometric block diagram

The block diagram fig 1 illustrates the two basic modes of a biometric system.[3] First, in verification (or authentication) mode the system performs a one-to-one comparison of a captured biometric with a specific template stored in a biometric database in order to verify the individual is the person they claim to be. Three steps are involved in the verification of a person. In the first step, reference models for all the users are generated and stored in the model database. In the second step, some samples are matched with reference models to generate the genuine and impostor scores and calculate the threshold. Third step is the testing step. This process may use a smart card, username or ID number (e.g. PIN) to indicate which template should be used for comparison. 'Positive recognition' is a common use of the verification mode, "where the aim is to prevent multiple people from using the same identity".

Second, in identification mode the system performs a one-to-many comparison against a biometric database in an attempt to establish the identity of an unknown individual. The system will succeed in identifying the individual if the comparison of the biometric sample to a template in the database falls within a previously set threshold. Identification mode can be used either for 'positive recognition' (so that the user does not have to provide any information about the template to be used) or for 'negative recognition' of the person "where the system establishes whether the person is who she (implicitly or explicitly) denies to be". The latter function can only be achieved through biometrics since other methods of personal recognition such as passwords, PINs or keys are ineffective.

The first time an individual uses a biometric system is called enrolment. During the enrolment, biometric information from an individual is captured and stored. In subsequent uses, biometric information is detected and compared with the information stored at the time of enrolment. Note that it is crucial that storage and retrieval of such systems themselves be secure if the biometric system is to be robust. The first block (sensor) is the interface between the real world and the system; it has to acquire all the necessary data. Most of the times it is an image acquisition system, but it can change according to the characteristics desired. The second block performs all the necessary pre-processing: it has to remove artifacts from the sensor, to enhance the input (e.g. removing background noise), to use some kind of normalization, etc. In the third block necessary features are extracted. This step is an important step as the correct features need to be extracted in the optimal way. A vector of numbers or an image with particular properties is used to create a template. A template is a synthesis of the relevant characteristics extracted from the source. Elements of the biometric measurement that are not used in the comparison algorithm are discarded in the template to reduce the file size and to protect the identity of the enrollee.

During the enrollment phase, the template is simply stored somewhere (on a card or within a database or both). During the matching phase, the obtained template is passed to a matcher that compares it with other existing templates, estimating the distance between them using any algorithm (e.g. Hamming distance). The matching program will analyse the template with the input. This will then be output for any specified use or purpose (e.g., entrance in a restricted area). Selection of biometrics in any practical application depending upon the characteristic measurements and user requirements. In selecting a particular biometric, factors to consider include, performance, social acceptability, ease of circumvention and/or spoofing, robustness, population coverage, size of equipment needed and identity theft deterrence. Selection of a biometric based on user requirements considers sensor and device availability, computational time and reliability, cost, sensor size and power consumption

Multimodal biometric:

Multimodal biometric systems use multiple sensors or biometrics to overcome the limitations of unimodal biometric systems. For instance, iris recognition systems can be compromised by aging irises and finger scanning systems by worn-out or cut fingerprints. While unimodal biometric systems are limited by the integrity of their identifier, it is unlikely that several unimodal systems will suffer from identical limitations. Multimodal biometric systems can obtain sets of information from the same marker (i.e., multiple images of an iris, or scans of the same finger) or information from different biometrics (requiring fingerprint scans and, using voice recognition, a spoken pass-code).

Multimodal biometric systems can fuse these uni-modal systems sequentially, simultaneously, a combination thereof, or in series, which refer to sequential, parallel, hierarchical and serial integration modes, respectively. Fusion of the biometrics information can occur at different stages of a recognition system. In case of feature level fusion, the data itself or the features extracted from multiple biometrics are fused. Matching-score level fusion consolidates the scores generated by multiple classifiers pertaining to different modalities. Finally, in case of decision level fusion the final results of multiple classifiers are combined via techniques such as majority voting. Feature level fusion is believed to be more effective than the other levels of fusion because the feature set contains richer information about the input biometric data than the matching score or the output decision of a classifier. Therefore, fusion at the feature level is expected to provide better recognition results.

Spoof attacks consist in submitting fake biometric traits to biometric systems, and are a major threat that can curtail their security. Multi-modal biometric systems are commonly believed to be intrinsically more robust to spoof attacks, but recent studies have shown that they can be evaded by spoofing even a single biometric trait.

2. RELATED WORKS

Domenick Poster, et.al,…[1] proposed novel approach to cross-spectral periocular recognition achieves state-of-the-art results using the proposed CoGAN architecture. Our experiments demonstrate that by introducing auxiliary intra-spectral image reconstruction tasks to support the effort of shared subspace feature learning for cross-spectral periocular recognition, the CoGAN attains higher performance over a baseline version of the model. The work presents the CoGAN architecture as a promising framework for further research in both intraspectral and cross-spectral periocular recognition, given the compact nature of its ResNet-18 backbone, lack of need for well-aligned image pairs, and potential for cross-spectral synthesis applications.

Fadi Boutros, et.al,…[2] motivated by the need for compact biometric deep learning models for deployment on resource-critical devices. Such models aim to have the capability to extract highly distinctive templates, as the larger models (more learned parameters) do. KD has been used to map such knowledge by teaching a smaller student model to produce a similar output as a larger teacher model. However, given that KD is commonly optimized on the classification output of such models, the knowledge of extracting biometric templates from pre-classification layers might not be optimally transferred to the student model. Therefore, we proposed a novel template-driven KD approach that aims at teaching the template extraction knowledge to the student model. The proposed approach was evaluated on smartphone periocular verification in intra- and cross-device settings. The achieved results showed that when the targeted small model was trained with our template-driven KD approach, it consistently outperformed similar models trained without KD or with the conventional KD approach.

João Brito, et.al,…[3] overview of ML interpretability was provided, along with a description of some of the most frequently cited techniques in this topic.

Additionally, a method that incorporates interpretability by design was discussed in detail. Overall, a twofold remark can be made: interpretability should be used in as many systems as possible and in the case of visual explanations, techniques such as LIME, SHAP or the method (for biometric recognition) deliver interpretability to otherwise black-box models. Therefore, in this document, focus on presenting the core principles of interpretability and describing the main methods that deliver visual cues (including one that we designed for periocular recognition in particular). Based on these intuitions, the experiments performed show explanations that attempt to highlight the most important periocular components towards a non-match decision. Then, some particularly challenging scenarios are presented to naturally sustain our conclusions and thoughts regarding future directions.

Joao Brito, et.al,…[4] described an integrated framework, based in well known deep-learning architectures, to simultaneously perform periocular recognition and - most importantly - to provide visual explanations of the regions/features that sustained every non-match decision, which we consider to be the cases where explanations are the most required. According to the powerful generative ability of GANs, we create a very large set of synthetic pairs that follow the "genuine distribution". At inference time, for every "impostor" comparison we are able to perceive the regions and features that failed the most (i.e., those that most evidently were different from a subset of the "genuine" synthetic pairs). This enables to generate pleasant explanations, where each component of the target region appears with a different colour depending on how it influenced the final decision. Importantly, the modular nature of our method ensures that the periocular region can be replaced by other biometric traits (e.g., the face) without compromising the explanations.

Lucia cimmino, et.al,…[5] focused on techniques for the extraction and the analysis of static periocular features, meaning the features coming from a single acquisition of the face. Recently, the analysis of periocular region gained a privileged position. COVID-19 pandemic has led several public health institutes worldwide to impose the use of facial masks to counter the transmission of the virus among people. Such restrictions represent a crucial factor for face recognition systems, which are nowadays adopted in several public areas as well as used as unlocking systems for personal mobile devices (e.g., smartphones and tablet). In this work, we focus the attention on the analysis of the periocular recognition aiming at discussing the contribution of the dynamics of the facial periocular features may introduce in biometric authentication systems. Macro- and micro-expressions can significantly transform the appearance and the distribution of facial features. Approaches based on a static acquisition could not well generalise the possible different appearances that an authorised identity might show over time. With this assumption, the proposed study explores the potentials and the robustness of analysing the dynamics of the periocular facial features through traditional Machine Learning classifiers.

Luiz A. Zanlorensi, et.al,…[6] proposed an attribute normalization scheme that can be used as a preprocessing step to reduce the within-class variability in unconstrained periocular recognition. The idea is to use state-of-the-art generative model that normalizes specific factors of all samples before being used by the recognition algorithm. Noting that our solution is fully agnostic to the recognition method used, our proof-of-concept was conducted in two datasets and five different baseline methods. Our idea was to compare the levels of performance attained by the recognition methods when using the raw data and when receiving the images pre-processed by solution. The observed results corroborated our hypothesis that the proposed attribute normalization is highly effective to reduce the within-class variabilities, without compromising the discriminability between classes, which is the root for the observed improvements in performance

Ritesh Vyas, et.al,…[7] deals with collaborative representation of near infra-red periocular images through traditional hand-crafted and end-to-end deep features. On one hand, hand-crafted feature descriptor is free from any sort of learning and/or hyperparameter tuning. While on the other hand, deep features are advantageous in terms of superior performance and facility of transfer learning. Hence, the current work focuses on extraction of both hand-crafted and deep features to study the potential of periocular recognition. The hand-crafted features are extracted through multiresolution and multi-scale analysis of the periocular image through a 2D Gabor filter bank, followed by calculation of local statistical measures from the image partitions. Whereas, deep features are extracted through fine-tuning of a popular CNN, namely ResNet-101, and extracting features from its deepest pooling layer. It has been observed from the experimental results that combined knowledge of hand-crafted and deep features can certainly lead to improvement in performance metrics. Notably, the system becomes applicable to highly demanding security venues, where lower FARs remain preferable.

Vineetha Mary Ipe, et.al,…[8] have addressed the approach of multispectral periocular recognition from a deep learning perspective. Our experiment shows that there is significant improvement in recognition performance by the application of off-the shelf CNN features. There are various open questions and challenges regarding the deployment of deep learning to the problem of periocular recognition, even though CNN such as Alexnet is effective in encoding discriminative features for periocular recognition. The computational intricacy of CNNs used for recognition task can be addressed by using model reduction techniques such as pruning and compression. The low accuracy for near infrared images can be addressed using super-resolution, a technique for improving the resolution of images. Also, this deep learning approach can also be extended to cross-spectral periocular recognition. Recent developments in Deep Reinforcement Learning and Evolution Theory allow the networks to adapt themselves and achieve better results for the task of periocular recognition.

Vedant Kayande, et.al,…[9] built two different models using convolutional neural networks and with the help of transfer learning that can have a pragmatic use in recognising and classifying users based on the periocular region of the face. We built the classifier of the two models each for the left and the right eye. The accuracy varies vastly because of the lighting conditions that lead to less number of features to be extracted. Also, we only consider the frontal images and discard other eye images which improves the accuracy of both the models but also acts as a limitation as the users are required to face into the camera directly without moving their eyes. The usage of Haar cascade in detecting the size of the eye and its region to keep the size of the images uniform is discussed. The proposed methodology of using two separate models for left and right to predict the participant id has been tested on constrained conditions i.e. only on front view images with the eye ball looking straight at the camera. The accuracy would certainly drop if tested on unconstrained data. Moreover, the model is unable to correctly classify participants wearing spectacles. More testing needs to be done on using cross dataset validation which is currently not possible due to lack of datasets of the periocular region specifically

Veeru Talreja, et.al,…[10] presented a periocular recognition framework based on a convolutional neural network (CNN) architecture and the fusion of soft biometric features with periocular features. The utility of this framework is that, due to the fusion of soft biometrics and periocular features, along with end-to-end model training, the soft biometric features enhance the discriminative power of the network and therefore improve the overall periocular recognition performance. We observed an improvement in EER of at least 3% in the open-world setting verification performance and an improvement in Rank-1 accuracy of at least 2% in the closed-world setting, when compared to the state-of-the-art methods. We have also evaluated the soft biometric prediction performance and observed an improvement of at least of 1.5% in accuracy due to the fusion of periocular features with the soft biometric features.

3. CONVENTIONAL APPROACHES

Using the periocular region to perform biometric recognition has recently gained popularity. By acquiring a region that is similar to that used by iris recognition systems, the key insight is to use not only the discriminating information inside the iris, but also all of the textures from the skin near the eye as well as the shape of the eyelid, the eyebrow and the eyelashes. Over the past few years, identity verification based on facial or eye features has gained a lot of prominence. Several works in literature have suggested novel features and classification techniques that can be used in the case of both these modalities in order to improve their performance. However, most of these approaches work under the implicit assumption that we are able to capture either a very good quality iris image (in the case of iris recognition) or that we are able to capture the entire face of the subject (in the case of face recognition). In such cases it would be very useful to investigate the viability of using only certain portions of the face as a biometric. Specifically, we consider the periocular region of the face, which is rich in texture - eyebrows, eye folds, eyelid contours, amongst others. This could be useful for instance when the person is wearing a mask where he/she exposes only the eyes, or if harsh illumination conditions expose features only in certain portions of the face. Ocular biometrics has made rapid strides over the past few years primarily due to the significant progress made in iris recognition.

4. MULTIMODAL BASED AUTHENTICATION SYSTEM

Multi-modal biometrics is systems that are capable of using more than one physiological or behavioral characteristic for enrollment, verification, and identification. Human identification based on multi-modal biometrics is becoming an emerging trend, and one of the most important reasons to combine different modalities is to improve recognition accuracy. There are additional reasons to combine two or more biometrics such as the fact that different biometric modalities might be more appropriate for unique deployment scenarios or when security is of vital importance to protect sensitive data. Some of these limitations can be addressed by deploying multimodal biometric systems that integrate multiple biometric modalities in a single scan to alleviate the challenges of a uni modal system. First, we form a tangent space from a set of perturbed images and observe that the tangent space admits a vector space structure. Second, we embed the approximated tangent spaces on a Grassmann manifold and employ a chordal distance as the means for comparing subspaces. The matching process is accelerated using a course to fine strategy. Recently periocular biometrics has drawn lot of attention of researchers and some efforts have been presented in the literature. In this project, we propose a novel and robust approach for periocular recognition. In the approach face is detected in real time face images which is then aligned and normalized. We utilized entire strip containing both the eyes as periocular region. For feature extraction, we computed the magnitude responses of the image filtered with a filter bank of complex curvelet transform. Feature dimensions are reduced by applying Grassmann algorithm. The reduced feature vector is classified using Convolutional neural network. The proposed work is shown in fig 2.

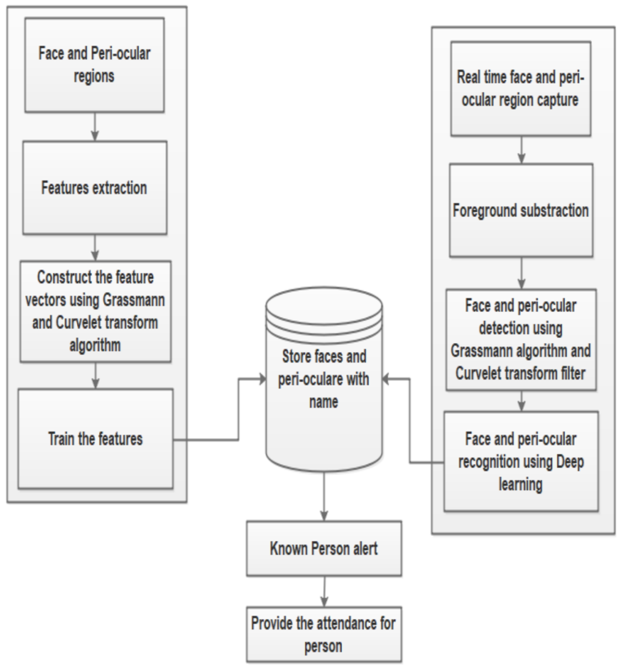

Fig 2: Proposed architecture

5. GRASSMANN ALGORITHM

The Grassmann manifold is a type of Grassmann manifold. The set of m-dimensional linear subspaces of the R D is known as G(m, D). The G(m, D) is a compact Riemannian manifold with m(Dm) dimensions.

An orthonormal matrix Y of size D by m can be used to represent an element of G(m, D), with Y = Im, where Im is the m by m identity matrix. For instance, Y may represent the m basis vectors of a set of R D photographs.

However, the matrices Y1 and Y2 are considered the same if and only if span(Y1) = span(Y2), where span(Y) signifies the subspace spanned by the column vectors of Y. In other words, if and only if Y1R1 = Y2R2 for some R1, R2 O, span(Y1) = span(Y2) (m). With this understanding, we will frequently use the notation Y to refer to its equivalence class span(Y), and Y1 = Y2 to refer to span(Y1) = span(Y2).

The length of the shortest geodesic connecting two points on the Grassmann manifold is the Riemannian distance between two subspaces. However, utilising the principal angles to define the distances is a more intuitive and computationally efficient method.

Input: A set of P points on manifold

$\{X_i\}_{i=1}^{P} \in G(d, D)$

Output: Karcher meanμK

1. Set an initial estimate of Karcher mean $\mu_K = X_i$by randomly picking one point in $X_i\}_{i=1}^{P}$

2. Compute the average tangent vector

$A = \frac{1}{P}\sum_{i=1}^{P} \log_{\mu K}(X_i)$

3. If $||A|| <$ ε then return μK stop, else go to Step 4

4. Move μK in average tangent direction $\mu K = \exp_{\mu K}(\alpha A)$, where$\alpha > 0$ is a parameter of step size. Go to Step 2, until μK meets the termination conditions (reaching the max iterations, or other convergence conditions

6. CURVELET TRANSFORM

Curvelet transform is a multi-scale and multi-directional transform with needle shaped basis functions. Basis functions of wavelet transform are isotropic and thus it requires large number of coefficients to represent the curve singularities. Curvelet transform basis functions are needle shaped and have high directional sensitivity and anisotropy. Curvelet obey parabolic scaling. Because of these properties, curvelet transform allows almost optimal sparse representation of curve singularities. The curvelet transform at different scales and directions span the entire frequency space. So, curvelet transform was designed to represent edges and other singularities along curves much more efficiently than traditional transforms, i.e., using fewer coefficients for a given accuracy of reconstruction. Curvelet transform is a ridge transform added with binary square window [8], which means subdividing a curve into approximate straight enough to carry out ridge transform. However, there exists big data redundancy in the transform. Therefore, improving the first generation curvelet transform can obtain the 2nd generation, and the second takes on features of faster computation and less redundancy.

7. CONVOLUTIONAL NEURAL NETWORK ALGORITHM

A Convolutional neural network (CNN)is a type of artificial neural network that has one or more convolution layers and are used mainly for image processing, classification, segmentation and also for other auto correlated data. Deep learning is a machine learning based artificial neural network that recognize objects in image by progressively extracting features from data through higher layers. As shown in figure in order to recognize face in an image we have to train the CNN with human faces. The benefit of using CNNs is their ability to develop an internal representation of a two- dimensional image. This allows the model to learn position and scale of faces in an image. After train the CNN it can able to recognize face in an image One can effectively use Convolutional Neural Network for Image data. CNN that extracts features in an image

Step 1: An image is nothing but the 2-dimensional array. Before training an image, we need to process the dataset. By processing the dataset, we mean converting each image in to NumPy array. Each row represents an image. NumPy package is inbuilt function. Datasets is completely ready to be trained by the model.

Step 2: Neural networks are like layers. Each layer of neural network contains nodes which calculates some values based on characteristics or weights. Activation function are Relu for hidden layers and either sigmoid or SoftMax for output layers.

Step 3: Convolution layer is a fundamental mathematical operation that is highly useful for to detect features of an image. In this layer we pass kernel. i.e., n*n matrix over the image pixel. Kernel has values in each of cell. It processed with original image help to produce some characteristics which help to identify images of the same object while predicting.

Step 4: Max Pooling operation involves sliding a 2-dimensional filter over each channel of features map and extract maximum features from image. Pooling layer used to reduce the dimension of feature map. It reduces the number of parameters to learn and amount of computation to perform. Pooling layer

Step 5: Flattening: Flattening operation is performed when we got multidimensional output and we want to convert in to a single long continuous linear vector.

The flattened matrix is fed as input to the fully connected layer

Step 6: Fully Connection Layer: It is one of the fully feed forward neural network. It formed by last few layers. Once the image is convolved, pooled and flattened, the result is a vector. This vector act as the input layer for an ANN which then works normally to detect the image.

8. CONCLUSION

Unimodal biometric systems fail due to lack of biometric information for a particular feature. Thus, it is robust to use multimodal biometrics for providing greater authentication. This review observed that multimodal biometrics authentication solve the issues in unimodal biometrics system such as interclass similarities, noisy data, and non-universality. In multimodal biometric, the biometric identifiers are fused based on feature extraction level, matcher score level and decision level. In this project, the various existing techniques used for the face and ocular multimodal biometric system have been reviewed. The primary objective of this project is to provide an explanatory view of periocular biometrics literature and about what features, feature extraction methods and matching schemes are already explored and what issues are remaining to be unexplored in this field. With the fast-growing technological world, it is necessary that the system used for identification and verification of the per-sons must ask for less user cooperation and periocular biometrics is a very good solution for this problem. Periocular region can be considered as a very promising trait both as a single modality and as a support for face and iris biometric. Periocular region achieved better result in many cases where face biometric suffers from different constraints like pose, illumination variation, occlusion and aging effect. Fusion of iris and periocular region also achieved better results as compared to iris as a stand-alone modality.

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