Todo list

Noget med Computer Vision

Project Report

Group 18gr842

Aalborg University
Vision, Graphics and Interactive Systems

This report is compiled in LaTeX. Additionally is Mathworks MATLAB, Adobe Illustrator, Lucidcharts.com, Inkscape, and Autodesk Eagle used to draw figures, schematics, and charts.

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Preface

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Chapter 1

Introduction

The problem of protection of physical elements or information by limiting the access to only the people is well known. The central challenge to the problem of security is the challenge of verifying the identity of a person trying to acquire access. The emergence of biometric techniques has induced an increasing interest in biometric-based security rather than knowledge-based or token-based security. This is mainly due to the fact that the more traditional methods for security systems are easier breached or spoofed [Ross and Jain, 2003]. Through the last decades researchers have investigated identity verification based on different biometric modalities. In the last decade investigations have been conducted in combining several biometric modalities in one system with the purpose of creating a system that performs better than the ones only utilising a single one. Results shows that combining modalities performs better than any of the modalities seperately [Chen and Te Chu, 2005]. However, increased accuracy is not the only benefit of utilising multiple biometric traits. More modalities increases the universality of the system and decreases the influence of noisy measurements [Ross and Jain, 2003].

One of the fields where biometric-base security is increasingly applied is security for handheld devices such as smart phones. Although technology is advancing and mobile devices are equipped with still more advanced components, the computing power and the quality of the data from sensors, are both constrains of mobile devices. These limiting factors makes it more challenging to make successful biometric-based identity verification on mobile devices rather than in other applications.Though the use of machine learning for image processing is well known, it has only scarcely been applied on data obtained by cameras on mobile devices. **?** presents different machine learning methods applied on iris images obtained by smartphone. Bazrafkan et al. [2017] applies deep learning for segmentation purposes on a database containing images acquired using a smart phones among others.

add source?

The work described in this report strives to make a system for identity verification based on multiple biometric traits for use on mobile devices. The biometric traits used are the iris and face. More specifically, this choice is made due to the arguments

describe more challenges (found in literature) before talking plan for solution argue some more

found in literature that iris is very distinctive, while face is non-invasive [Wang et al., 2009].

Chapter 2

Research

Hat

Face Recognition

The first computer based face recognition was made in 1973. This was based on a feature approach, meaning the program identifies basic face features such as mouth, eye, and nose placement. From here three different types of approaches were made, namely a holistic, feature extraction and a hybrid approach.

The holistic approach encodes the entirety of a face and then identifies using template-matching, the feature extraction approach extracts a defined amount of features from the face, whereas the hybrid method uses both template-matching and feature extraction [Wechsler, 2007]. In 1990, Principal Component Analysis (PCA) was introduced for holistic face recognition. The PCA approach makes use of eigenfaces, each eigenface represents a component a face is encoded. But as Wechsler [2007] claims, Linear Discriminant Analysis (LDA) is a more effective suitable approach for face identification and authentication. Another holistic approach is using support vector machines (SVM) for face recognition [Wechsler, 2007].

The feature approach gave way for what is now known as recognition-by-parts, which uses the features and a global structure to link these features. A structure for linking 2D features is the Hidden Markov Model (HMM). PCA is also used in this approach, but is used to model shape or texture of the face.

Niclas: We need an "introduction" to the subsection

DeepID

Deep hidden identity features (DeepID) is a Convolutional Neural Network (CNN) which aims to use feature extraction for face identification and verification. It detects five facial landmarks; the two eye centres, the nose tip, and the two mouth corners. The network is made of four convolutional layers with max-pooling, which are used to extract features hierarchically. These are followed by the fully-connected DeepID layer and a softmax output layer to indicate identity classes. The feature extraction and recognition is done in two steps, where the first feature extraction is learned with the target of face identification [Sun et al., 2014a].

In the CNNs the neuron number of the last hidden layer in the network is much smaller than that of the output layer. This is done, to better classify faces [Sun et al., 2014a]. The network extracts low-level features in the bottom layers, where feature numbers decreases for each layer. In opposition, the high-level features are formed in the top layers.

The network is tested using the Labeled Faces in the Wild (LFW) database. This database is images of faces from different angles and scenarios consisting of 13.233 images [Huang et al., 2007]. It achieves 97.45% accuracy on this dataset, requiring weakly aligned faces [Sun et al., 2014a].

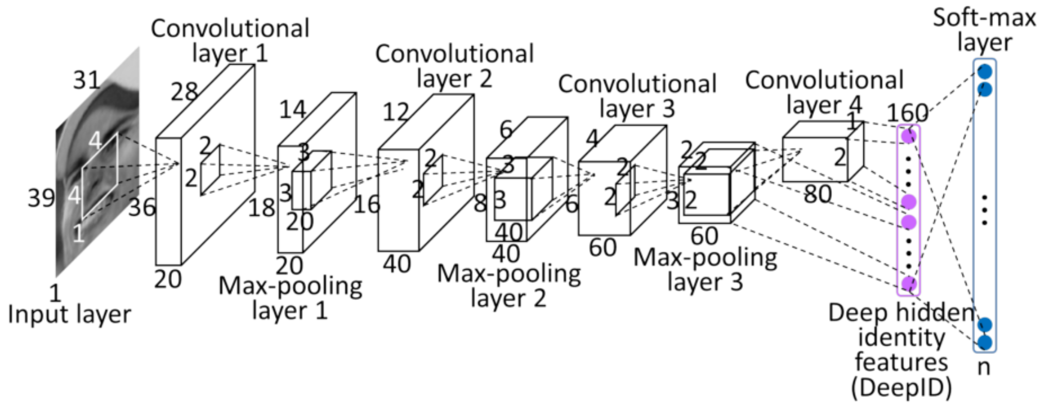


Figure 2.1: Structure of the CNN used in DeepID [Sun et al., 2014a]

DeepID2

Deep IDentification-verification features (DeepID2) is an expansion upon DeepID and is a deep Convolutional Neural Network used for face identification and verification. This is done by using feature extraction.

Just like DeepID, DeepID2 uses four convolutional layers but only the first three uses max-pooling. It uses 400 face patches instead of 60 [Sun et al., 2014a,b] and detects 21 landmarks of the face.

The DeepID2 layer is after the four convolutional layers. This layer is learned under two supervisory signals. The first is identification classifying the images into identities. The second is face verification which manipulates the DeepID2 data to be similar to a matching identity should this be the same.

DeepID2 also uses the LFW database and achieves a 99.15% accuracy.

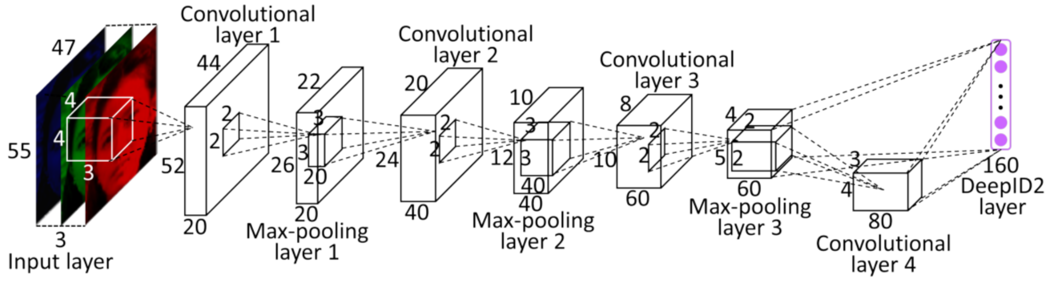


Figure 2.2: Structure of the CNN used in DeepID2 [Sun et al., 2014b]

DeepID3

DeepID3 is a further expansion of both DeepID and DeepID2 but is also drawing on some from elements from VGG net and GoogleNet [Sun et al., 2015]. The qualities from these two networks is the use of stacked convolution and inception layers. DeepID3 is in general a deeper network than DeepID2 and its expansion DeepID2+.

DeepID3 resembles DeepID2 in the use of adding supervisory signals to early layers.

Sun et al. [2015] proposes two different networks with DeepID3. One is using eight convolutional layers with max pooling after every other convolutional layer. The second network has four convolutional layers with max pooling after every other, following are five inception layers.

DeepID3 is also tested on the LFW dataset with an accuracy of 99.52% which is an increase in accuracy compared to DeepID2, but as stated in Sun et al. [2015] it is not an improvement of DeepID2+.

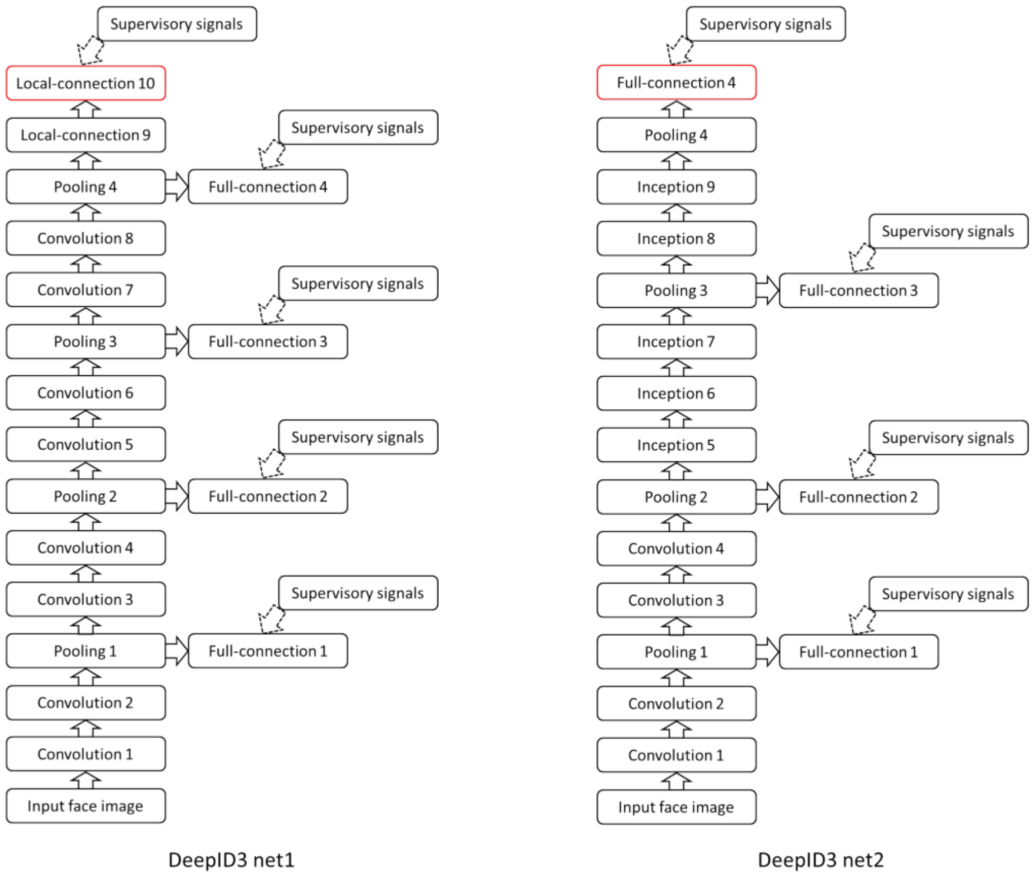


Figure 2.3: Structure of the CNN used in DeepID3 [Sun et al., 2015]

Iris Recognition

Modern iris recognition was first introduced in an article by Daugman [1993] discussing the security of using iris for recognition. Here an outline of how to do recognition was laid out and even though the field has been extensively since, the general methodology is more or less the same as Daugman proposed. A modern system is typically composed of image acquisition, segmentation and normalisation, feature extraction and matching.

extensively what?

Images

The images acquired are often taken in the Near Infra-Red (NIR) spectrum, which is ranging between 700 nm and 900 nm in wavelength. In this band, the melanin in the iris, which is the substance that gives the iris its colour e.g. brown or blue, is typically less prominent making the unique structure in the iris very distinct. To acquire usable NIR images, the user has to be in the millimetre range of the NIR camera. In the visible light, the melanin is much more prominent and thus makes is harder to detect the structure. The band of visible light has many names in the literature, namely Visible Spectrum (VIS), Visible Wavelength (VW), and Visible Light (VL). VL will be used in this report. While NIR is beneficial in some cases, other useful features can be observed in the VL that cannot be seen with NIR. These can include the moles, freckles and conjunctival vasculature, which can help in making more accurate recognition systems. To make iris recognitions systems comparable with each other some publicly available databases are often used. Rifaee et al. [2017] give an outline of the some of the free databases that are used. A comprehensive table summarising the visual properties, statistics and type of subject used in various database are tabulated in Figure 2.4 and Figure 2.5. Most of the databases available are NIR images with CASIA being one of the most used database. For VL images, UBIRIS in the most commonly used. These contain more "real world" data as the images contain more noise in the form of eyelids obstruction, eyelash obstruction, glare, motion blur, out-of-focus or poor focused iris, partial iris and specular reflection [Rattani and Derakhshani, 2017]. The database has also been used in Noisy Iris Challenge Evaluation (NICE) I. The increasing usage of mobile devices also proposes an opportunity to integrate iris recognition as a biometric for verifying the identity of the user. For this purpose a competition, Mobile Iris CHallenge Evaluation (MICHE), is made to compare the state of the art mobile iris. They provide a the MICHE database that can be used, which they claim is a better database than UBRIS for mobile systems. The database contains noisy iris images taken with a Galaxy Samsung IV, iPhone 5, and Galaxy Tablet II. The noise includes noise from both artificial and natural light sources during acquisition, motion blur, occlusion due to eyelids, glasses, eyelashes, hair, or shadows, which can naturally occur when a user is trying to unlock a phone using their iris.

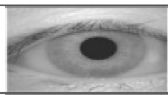
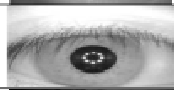
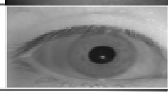
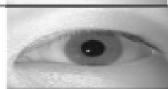
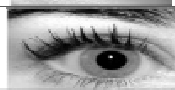
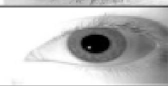
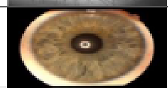
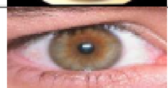
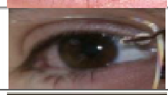
Database name	Database size	Light wave length	Varying distance	Camera	Sample image
CASIA v1	756	NIR	No	CASIA camera	
CASIA v2	2,255	NIR	No	CASIA camera	
CASIA v3	22,051	NIR	No	OKI iris-pass h	
CASIA v4	2,576	NIR	Yes	IKEMB-100 dual camera	
Bath	16,000	NIR	No	ISG LW 1.3 S 1394	
MMU 1	450	NIR	No	LG EOU 2200	
MMU 2	995	NIR	No	Panasonic BM ET 100 US	
ICE 1	2,900	NIR	No	LG EOU 2200	
ICE 2	75,000	NIR	No	LG EOU 2200	
WVU	3099	NIR	No	OKI iris-pass h	
UPOL	384	Visible	No	Sony DXC 950P 3CCD with TOPCON TRC501A	
UBIRIS v1	1877	Visible	No	NIKON E5700	
UBIRIS v2	11,357	Visible	Yes	Canon EOS 5D	
FRGC	50,000	Visible	Yes	Minolta Vivid 900/910	

Figure 2.4: A table depicting the contents of free iris image databases [Rifaee et al., 2017].

Database	Noise													
	Eyelashes	Eyelids	Specular Reflection	Light Reflection	Motion Blurred	Poor Focus	Gaze Deviated	Partially Occluded	Out of Iris	Over Distance	On The Move	Rotated	Glasses	Visible Wavelength
CASIA 1	√	√	-	-	-	-	-	-	-	-	-	-	-	-
CASIA 2	√	√	-	-	-	-	-	-	-	-	-	-	-	-
CASIA 3	√	√	-	-	-	-	-	-	-	-	-	-	-	-
CASIA 4	√	√	-	-	√	√	√	√	-	√	√	√	-	-
BATH	√	√	-	-	-	-	√	-	-	-	-	√	-	-
MMU 1	√	√	-	-	-	-	-	-	-	-	-	-	-	-
MMU 2	√	√	-	-	-	-	-	-	-	-	-	-	-	-
ICE 1	√	√	-	-	-	-	√	-	-	-	-	√	-	-
ICE 2	√	√	-	-	-	-	√	√	√	-	-	√	-	-
WVU	√	√	-	-	√	√	√	√	-	-	√	√	-	-
UPOL	-	-	-	-	-	-	-	-	-	-	-	-	-	√
UBIRIS.v1	√	√	√	√	√	√	√	√	√	-	-	√	√	√
UBIRIS.v2	√	√	√	√	√	√	√	√	√	√	√	√	√	√
FRGC	√	√	√	√	√	√	√	√	√	√	√	√	√	√

Figure 2.5: A table depicting the noise present in the databases [Rifaee et al., 2017].

Segmentation

Segmentation of an iris in iris recognition systems tries to detect the iris and find the pupillary boundary and the limbus boundary as well the eyelids and eyelashes that can cause noise on the image. The boundaries along with other parts of the iris can be seen in Figure 2.6. The approach used for segmentation depends among other things on the wavelength of the image; NIR or VL. They both have some common challenges to them. Often the eyelids can cover a small part of the iris, causing the limbus boundary of the iris to not be circular or elliptical. Eyelashes can also cause a similar disturbance as they also can cover parts of the iris. Poor lighting can also make it extremely difficult to detect the boundaries. Specular reflections in the iris can also cause difficulties as they can lie on the iris boundary or close to. Most systems also require a great deal of user cooperation as an off angle iris, motion blur, or glasses or contact lenses can make it even more difficult to detect the boundaries. This can especially be the case for iris recognition in a phone as it cannot be expected of the user knows how to acquire a good iris image.

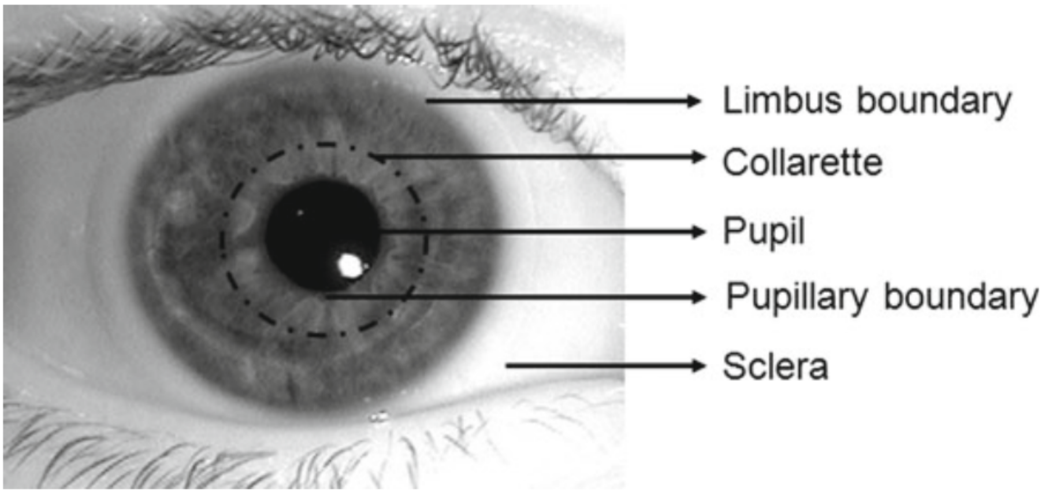


Figure 2.6: A close up NIR image of an iris depicting the different parts of the iris along with their names [Connaughton et al., 2016]

Two commonly observed approaches for segmentation in NIR band images are Daugman's approach [Daugman, 1993] , [Saha et al., 2017], [Rattani and Derakhshani, 2017], [Khan et al., 2017], and Hough Transform [Luhadiya and Khedkar, 2017], [Uka et al., 2017]. Daugman's approach consists of using a Gaussian filter on the image to attenuate the effect of noise and eliminate undesired weak edges like the boundaries within the iris while keeping the strong edges like iris boundaries and eyelid boundaries. An integro-differential operator is then used as a circular edge detector. It is then used iteratively to find the pupillary boundary and the limbus boundary. Hough Transform on the other hand is a histogram based model fitting approach. An edge map of the input map is generated using a gradient-based edge detector. Then a voting procedure is applied on the thresholded edge map to determine the parameters for a contour that best fits a circle. This operation gives an approximate edge map of the iris boundary. Lastly, the segmented iris is often normalised using Daugman's rubber sheet model that maps every point in the segmented region from cartesian to polar coordinates. An open source MATLAB implementation based on updated version of the Daugman approach is a commonly used tool. There exist other methods for different circumstances, but these are two most commonly used. They can also be used on VL images if the image is converted from RGB to grey scale images [Connaughton et al., 2016] .

Remember to add a proper citation

How to properly cite a book where each chapter is written by different people?

Feature extraction and classification

There are multiple ways that the features can be extracted from the segmented iris. The most commonly used in the literature is a 2D Gabor filter which is a linear filter used for edge detection [Daugman, 1993]. The Hamming distance is then used as way to classify the iris. The Hamming distance is a measurement of how many bit flips a piece of data need to have to match another piece of data. The bits of the extracted features are then measured against the whole database and the pair with the lowest score is a match. This is called "1-to-N search". As the database gets larger and larger the computation time also grows as it will have to search through the whole database. That's why Kuehlkamp and Bowyer [2016] have suggested using a "1-to-first search" instead to improve the speed of the search. Here a threshold is chosen and as soon as a match has been found below the threshold it will stop the search. Other approaches to the categorisation have been proposed using machine learning. Khan et al. [2017] proposed using SVM, K-Nearest-Neighbours (KNN) and LDA with respective test accuracies of 97%, 95.1%, 94.28%. In comparisons the commercial systems ranged from 94.57% to 99.67% with VeriEye having the lowest and IriCore having the highest accuracy.

Deep Learning

According to Zhao and Kumar [2017] research in neural networks within iris recognition is still very new and not much has been done. Some of the work that has been done have used CNN and a Deep Belief Network (DBN). Al-Waisy et al. [2017b] used a common CNN to extract features and classify a segmented and normalised iris image. The segmentation was done using Circular Hough Transform (CHT) normalisation was done using Daugman's rubber sheet method. They named the network IrisConvNet and the architecture was inspired by the Spoofnet as it can be seen in Figure 2.7. This was the general architecture and they tried different numbers of maps and layers to find the best architecture. In general a 3x3 input kernal was used on a 64x64 or 128x128 pixel input image to create feature maps followed by 2x2 max pooling, 5x5 convolution, 2x2 max pooling 5x5 convolution, 2x2 max pooling, 5x5 convolution and finally a two fully connected layers to to a softmax regression classifier layer. A ReLU activation function is applied on the top of the convolutional and fully connected layers because it results in several times faster training without sacrificing accuracy. The AdaGrad algorithm was used for training the network. Three databases were used; SDUMLA-HMT, CASIA-Iris-V3 and IIT Dehli (IITD).

maybe add a source or explanation if needed?

IrisConvNet scored an accuracy of 99.82% at categorising CASIA-Iris-V3 in 0.65 s. architecture

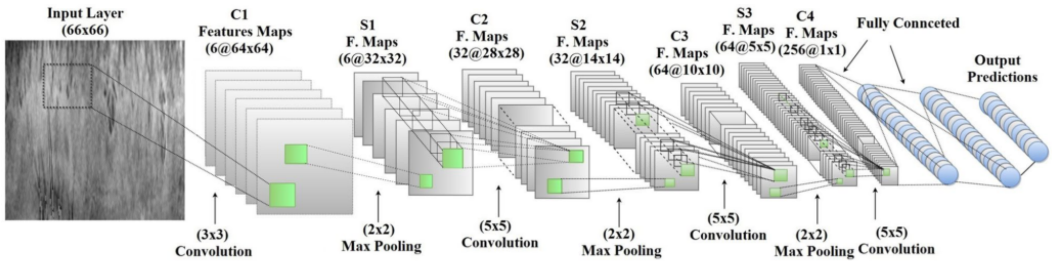


Figure 2.7: Example of a CNN architecture from Al-Waisy et al. [2017b].

IrisCode? what is this?

Zhao and Kumar [2017] claim that the problem with traditional networks are that they are database specific and not very generalisable. They created a Fully Convolutional Network (FCN) using a loss function they created specifically for iris networks called Extended Triplet Loss (ETL). They claim this network is more generalisable than the previous networks and it shows superior results compared with IrisCodewhich is Daugman's segmentation and normalisation approach. A FCN differs from a CNN in that there are no fully connected layers, only convolutional layers, max pooling etc. They proposed an architecture called UniNet that can be seen in Figure 2.8. It consists of two FCNs; FeatNet and MaskNet. The network takes an iris that has been segmented and normalised using a recent approach [Zhao and Kumar, 2015]. The segmented iris has a resolution of 64x512 pixels. The image is then fed through FeatNet and MaskNet. FeatNet extracts the iris features while MaskNet masks the non-iris part of the image. e.g an eyelid that occludes. Three of these UniNet networks are then trained in parallel in Triplet-based network architecture that uses the ETL loss function. They used four databases to train and the networks; ND-IRIS-0405, CASIA V4, IITD and WVU Non-ideal Iris Database. It was then compared with a CNN network based on VGG-16 that used softmax, CNN with triplet, FeatNet only and DeepIrisNet which is a CNN that is proposed directly for iris recognition. The results can be seen in Figure 2.9 where UniNet outperforms the other nets and FeatNet is the by far worst performing network, which suggests that MaskNet is needed for the network to perform well.

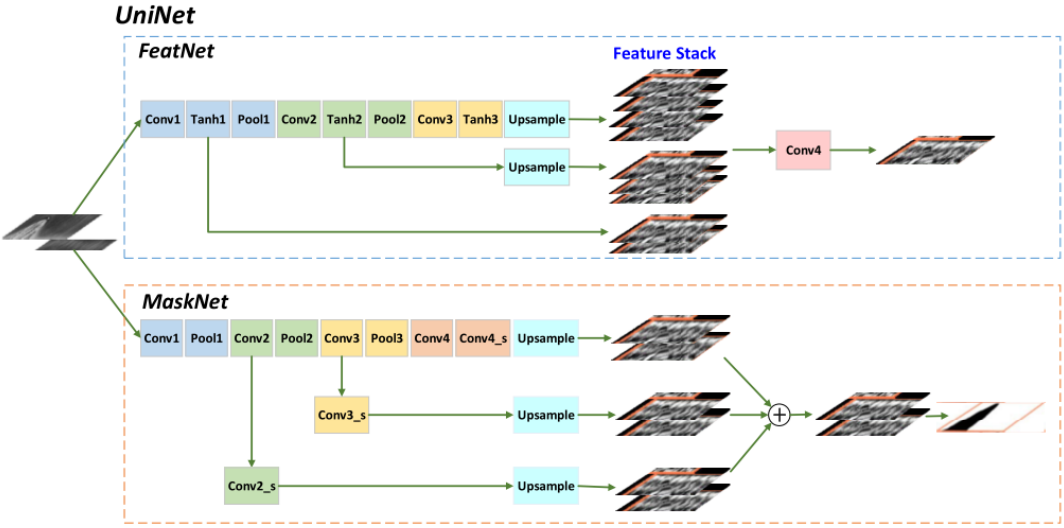


Figure 2.8: Example of a CNN architecture from **?**.

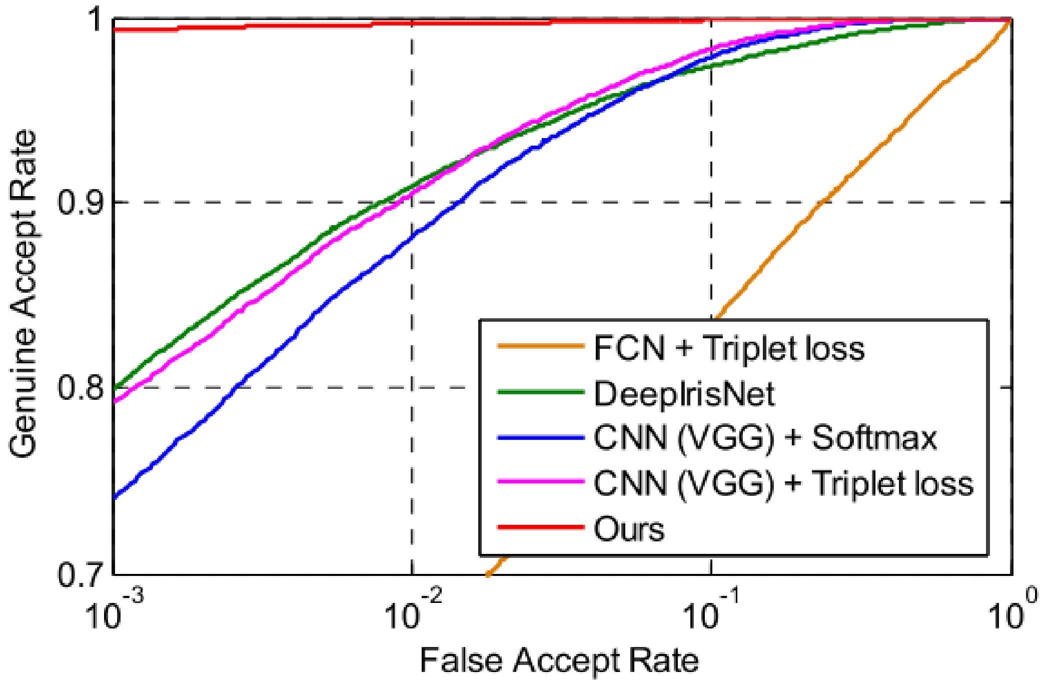


Figure 2.9: Results from the different networks tested on the ND-IRIS-0405 database **?**. "Ours" is UniNet and FCN + Tripletloss is FeatNet

Another promising approach by Bazrafkan et al. [2017] targets iris segmentation in low-quality consumer images obtained from smartphones is using Semi Parallel

Deep Neural Networks (SPDNN) for generating iris maps from low quality iris images. In SPDNN several deep networks are merged into a single model. This way it is possible to include different networks designs and combine their strengths. They combined four FCNs of different architectures that used a variaty of kernel sizes and layers. An example of one of the FCNs has 12 convolutional layers in this order; 3x3,5x5,7x7,9x9,11x11,13x13,15x15,13x13,11x11,9x9,7x7,5x5 and an output layer that is 3x3.It was trained by using the databases Bath800, CASIA Thousand, UBRIS and MobBio. They contained both NIR and VLimages. Extensive noise was also added to the training images in the form of blur and lower contrast to generate degraded versions of the high quality images and utilise the databases better by creating more samples. Using the UBRIS database as a comparison with other state of the art segmentation techniques it achieved the highest accuracy with 99.30%. The technique with the lowest accuracy, of the ones it was compared to, had an accuracy of 98.10%.

consider whether it makes sense to call it VL images rather than RGB images

Information Fusion

A system that strives to utilise information from two or more different biometric traits in order to obtain one combined result is a called a multi-modal system which is a kind of multi-biometric system. Besides the multi-modal approach there are several other approaches, which results in information from two or more sources, therefore, methods for fusion of information from different sources into one system for classification purposes is a widely investigated area. [Connaughton et al., 2016]

Fusion of information can happen on different levels. It can happen on one of five levels, each with a higher level of preprocessing: signal level, feature level, score level, rank level, or decision level. The level on which the fusion should be done depends on the kinds of multi biometric data that has to be fused, and the purpose of the fusing. In general score-level and feature-level are the most popular fusing techniques [Connaughton et al., 2016]. Fusing at the lowest level, signal level, might be done in order to merge data from different sources to construct a more detailed or larger dataset or signal. At the feature level the fusing might happen through merging of extracted features from different sources into one feature vector [Ross and Jain, 2003]. At the score level the fusion can be done in order to determining the best sample to use for the processing based on which has the highest score and thus is the best match to the gallery samples. Rank level can be somewhat similar to the scores but depend on match rankings. At the decision level it can be making the decision based multiple classifiers, e.g. one for each modality[Fierrez et al., 2018].

In the literature a large variety of methods and algorithms have been utilised for fusing information on different levels. Some algorithms are fairly simple and basically makes decisions about which sample to use onwards for classification based on matching scores between samples and the gallery. Other methods are more advanced and well known for use in applications such as classification. These are methods such as SVM, KNN, decision trees, and bayesian methods [Ross and Jain, 2003].

The highest rank method and Borda count are both well known methods for combining information based on ranking. The highest rank method ranks possible classes based on the highest rank assigned to the class by a classifier across all classifiers.[Ho et al., 1994] The Borda count is a kind of majority voting which can be used in combination with Multiple Classifier Systems (MCS) [Connaughton et al., 2016; Ho et al., 1994]. An important aspect to consider is that whenever different kinds of information are fused together, the information should be represented in the same data space, otherwise unwanted weighing of certain information above other might occur.

In this report, the focus is to implement a multimodal system utilising the biometric traits face and iris. In literature different approaches for the fusion of these traits have been presented. Al-Waisy et al. [2017a] as one of the lates researches within the area presented a work utilising deep learning for feature extraction and matching of the biometric traits and tests different methods for score and rank level fusion of the modalities. The tested methods on score level include eg. sum, weighted sum, max etc while the rank level fusion uses the mentioned Borda count, Highest rank, or Logistic regression.

Multi-Modal Databases

Even though recognition based on biometric traits is widely investigated, and research shows that multimodal systems perform better than the uni-modal systems based on the same data, the research in this area is limited and incomplete [Chen and Te Chu, 2005; Connaughton et al., 2016]. Because of the limited availability of multimodal datasets, such datasets are often synthetically constructed based on randomly combined data, eg. iris and face datasets [Chen and Te Chu, 2005]. Only a limited amount of studies utilise a multimodal dataset obtained from the same test subjects or maybe even with one sensor. However, a few multimodal datasets have been encountered in literature. The multimodal datasets varies in which modalities they include. The modalities can be different images of face, recordings of gait, hand geometry, handwriting, signature, fingerprint, finger vein, iris, speech etc. [Yin et al., 2011; Dessimoz et al., 2007; Ross and Jain, 2003; Ortega-Garcia et al., 2010]. Examples of multimodal datasets containing both iris and face are the database IV^2 [Petrovska-Delacrétaz et al., 2008], consisting of data obtained from 300 subjects, the MBioID based on 120 subjects [Dessimoz et al., 2007], The BiosecureID based on 400 subjects, The BioSec database based on 250 subjects, the BMDB DS2 based on 667 subjects [Ortega-Garcia et al., 2010], the SDUMLA-HTM database based on 106 subjects, the MobBio containing data from 105 subjects acquired through a mobile device [Sequeira et al., 2014],and the datasets provided for the The Multiple Biometric Grand Challenge (MBGC) [Connaughton et al., 2016]. The latter is available in two versions and can be obtained on request. Furthermore, it serves as a common test set in order to compare performance. However, some multimodal datasets have been created by researchers during their work, which are not named nor generally available [Connaughton et al., 2016].

Database Name	**Responsible**	**Number of Subjects**	**Database Content**
IV^2		300	
MBioID		120	
BiosecureID		400	
BioSec		250	
BMDB DS2		667	
SDUMLA-HTM		106	
MobBio		105	VL Iris VL Face voice
MBGC v1/v2			
Bowers			

Table 2.1: Multi modal biometric databases containing both iris and face information.

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