PURPOSE-LED
PUBLISHING™

PAPER • OPEN ACCESS

Cross-spectral Gender Classification Using Multi-spectral Face Imaging

View the article online for updates and enhancements.

The Electrochemical Society
Advancing solid state & electrochemical science & technology

ECS UNITED

247th ECS Meeting
Montréal, Canada
May 18-22, 2025
Palais des Congrès de Montréal

Early registration deadline: April 21, 2025

Unite with the ECS Community

Cross-spectral Gender Classification Using Multi-spectral Face Imaging

Narayan Vetrekar, Aparajita Naik, R. S. Gad

Department of Electronics, School of Physical and Applied Science, Goa, University, Taleigao-Plateau, Goa, India.

E-mail: `vetrekarnarayan@unigoa.ac.in`

Abstract. Soft biometrics has been gaining significant attention in biometrics literature for usage in recognition system. Gender classification is one such soft biometric traits that has been studied extensively using visible spectrum range and limited studies beyond visible spectrum. In this paper we present the cross-spectral gender classification using Multi-spectral imaging. We present this study using the facial images captured in nine narrow spectral bands ranging from $530nm$ to $1000nm$. Further, we present an extensive benchmark evaluation based on state-of-the art linear Support Vector Machine (SVM) classifier for facial discriminative features in the cross spectral data in a robust manner. The extensive evaluation results based on 10 fold cross-validation indicates the highest average classification accuracy of 92.84% for cross-spectral study.

1. Introduction

Soft biometrics traits such as age, gender, ethnicity, skin color, height etc, can be defined as behavioural, anatomical, physical or characteristic human identifiers that provides some information of an individual. However, this information is not sufficient to differentiate two different individuals [1] in an authentication system. The information deduced from the soft biometrics although may be insufficient in identifying a particular individual, it can help in reduction of the search space of a large biometric database (training database) and thus increasing the detection accuracy of identification system[2, 3]. Essentially, in the case of face recognition system, the amount of recognition accuracy can be significantly improved thereby reducing the amount of search time in the training database.

Amongst the different soft biometrics such as age, gender, ethnicity, skin color, height etc. gender classification has been extensively studied for applications in biometrics, surveillance, border crossing, and human computer interaction applications [4]. Gender is a soft biometric trait that is permanent and a stable attribute of an individual over a period of time. On the other hand, facial biometrics is immensely popular because its covert nature of image capture in a non-intrusive manner in surveillance scenario[4, 5]. For these reasons gender classification based on facial biometrics has been gaining significant popularity in biometric literature.

Gender classification is a two-class problem, which by analyzing facial features predicts, whether an input image belongs to female or male class [6]. This two-class information is especially important in applications such as surveillance, where gender information can add value or a soft label for an image captured in an unconstrained setting[7, 8]. Facial biometric based gender classification although widely studied has largely been done in the visible spectrum.

In real life situations, the accuracy of gender classification is a heavily degraded by the unconstrained lighting and thus there is recent studies move to perform gender classification beyond the visible spectrum [8]. Although, working beyond the visible spectrum essentially finds the importance in nighttime surveillance application, the challenge of cross spectral gender classification has still not given much attention in literature.

1.1. Literature Survey

Most of the public biometric surveillance systems installed today operate in the visible spectrum. Further, large scale public domain facial image database consists of images collected in the visible spectrum[7, 9]. Thus, much of the existing research in the line of gender classification has been conducted based on facial images acquired in the visible spectrum[10, 3]. Majority of the work in this line employed techniques such as holistic and part-based face image processing approach for gender classification with most of these approaches are based on texture descriptors [11] or dictionary-based descriptor [3, 12]. This was followed along with strong classifier like Support Vector Machine for gender prediction. The disadvantage of these methods is that they tend to be slow and computationally complex [3]. Recent studies have also shown the significance of Deep-Convolutional Neural Network on the large scale public domain visible spectrum facial image database gender classification[9, 10, 13]. Further, there are limited literature studying Near-Infra-Red (NIR) [8, 14] and Thermal spectrum[13], however these too were processed using texture based descriptor methods. As is evident from above, most of the research is focussed on using the public domain available facial database and the few recent works in NIR and Thermal Spectrum. In addition, majority of these methods use texture-based descriptor in conjunction with a strong classifier for gender classification.

With the considerable disadvantages of operating in the visible spectrum, the scope of multi-spectral imaging is being explored in face biometrics with great promise in recognition accuracy, especially in unconstrained environments. Multi-spectral imaging extracts the discriminative spatio-spectral features across narrow spectral bands of electromagnetic spectrum in discrete and disjoint manner. The key point is to leverage the complementary reflectance and/or emittance information due to variations in human skin photometric properties. These variations in photometric properties of a human skin across the gender are contributed by variation in chromosphere concentration presence in the sub surface skin [15]. Hence this optical feature of the human skin plays a significant role in discriminative gender classification problem. The potential of multi-spectral imaging have seen several works in this direction based on the inherent properties of individual spectral bands for gender prediction in this direction [16, 17]. Although, multi-spectral imaging has shown great potential in this direction, the cross spectral gender classification have still not address for its robustness.

Thus, in this work present a study using multi-spectral facial database for Cross-Spectral gender classification based on nine bands spanning from Visible (VIS) to Near-Infra-Red (NIR) wavelength range. Further, to present this benchmark evaluation study, we make use of a linear Support Vector Machine (SVM) classifier to perform the gender classification. We evaluate this approach on a multi-spectral facial database of images corresponding to 145 subjects collected across nine bands spanning from $530nm$ to $1000nm$ under illumination of a Quartz Tungsten Halogen (QTH) lamp. The experiment is then repeated to perform 10 fold cross-validation, where the number of samples in training and testing dataset under each fold or trial has been selected in a random and disjoint manner to determine the mean accuracy. The major key contributions of this paper can be summarised as follows:

- Introduces the cross-spectral gender classification thereby exploring multi-spectral facial database acquired in nine narrow spectral bands covering Visible and Near-Infra-Red spectrum.

- Presents benchmark study based on large scale multi-spectral face database of 145 subjects for gender classification.
- Present an extensive evaluation thereby employing 10 fold cross-validation for gender prediction.

The rest of the paper is organised in the following manner: Section 2 describes in detail the multi-spectral facial database used in this work for gender classification and the image preprocessing, Section 3 presents the detailed methodology employing cross-spectral matching along with state-of-the-art linear Support Vector Machine (SVM) classifier to perform the prediction, Section 4 presents the benchmark evaluation results in the form of average prediction accuracy thereby repeating the experiment for 10 time, and finally, the conclusion along with future work is discussed in the Section 5.
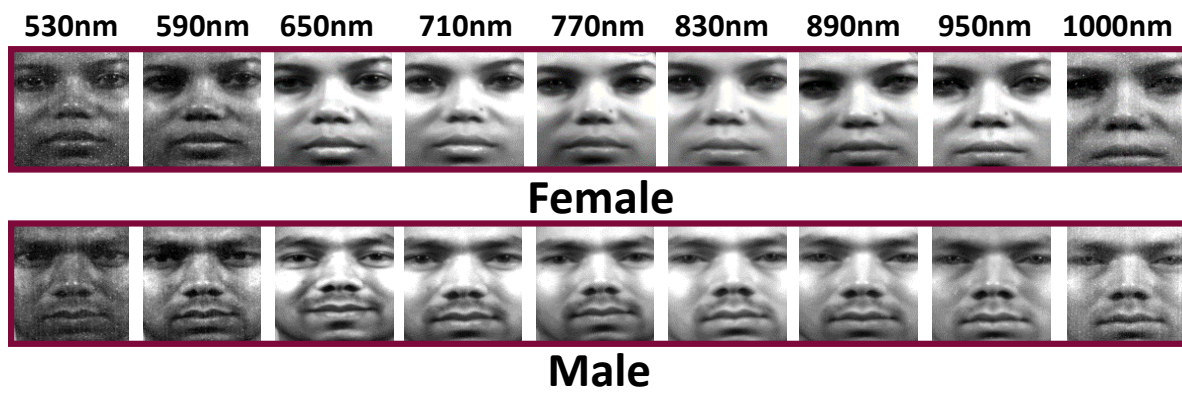

Figure 1. Sample Multi-spectral face database collected using Quartz Tungsten Halogen(QTH) lighting across nine narrow spectrum bands.

2. Multi-spectral Database

The Multi-spectral face database used in this experiment is imaged using an in-house custom designed spectral imaging sensor. Facial images of 145 subjects were captured which included 87 male and 58 female subjects. The facial images of the 145 subjects are imaged in nine narrow spectral band images ranging from Visible (VIS) to Near Infra-Red (NIR). These correspond to the following nine bands: $530nm$, $590nm$, $650nm$, $710nm$, $770nm$, $830nm$, $890nm$, $950nm$, and $1000nm$. The facial images acquired under this database is in six different conditions: five in indoor lighting conditions and one in outdoor lighting conditions. Five indoor illumination conditions were based on three different light light source such as Quartz Tungsten Halogen (QTH), Xenon, Incandescent bulbs, and their combination. For simplicity and to perform cross-spectral gender classification, we have used only the sample multi-spectral facial database collected under QTH light source. Further, it consists of sample images acquired in two different sessions with a time interval of three to four weeks in between. Each session consists of five sample facial images collected for nine narrow spectrum bands. The total number of sample images collected under this set of illumination condition is 145 Subjects× 2 Sessions × 5 Samples × 9 Bands = 13050 sample spectral images. The detailed summary of number of sample multi-spectral images are given in Table 1.

2.1. Face Image Pre-Processing

The facial spectral band images are high dimensional images of size 1024 × 1280. The facial images are first normalized that correct the presence of any rotation and translation of the face

Table 1. Detailed summary describing the number of sample images collected using multi-spectral imaging sensor

Subject	Sessions	Samples	Bands	Total
145	2	5	9	13050

images. These corrections are established using the eye co-ordinates that are detected from a face landmark detection algorithm [18]. In addition to the component of the face image, unwanted information in the form of background and part of torso is also captured. Thus, the normalized image captured is segmented to discard this unwanted information and resized to 120×120 resolution which reduces the computational load. Further, we employed histogram equalization method to enhance the spectral band features on the cropped facial images across individual spectral face image. The sample multi-spectral face images can be seen from Figure 1.

3. Methodology

This section of paper, we detail the methodologies employed in this paper for cross-spectral gender classification using the multi-spectral face database. Multi-spectral facial images are collected in nine narrow spectral bands, hence to perform cross-spectral study, we employed one of the spectral band (say $530nm$) to learn the characteristic features from an image using Support Vector Machine Classifier (SVM) and perform the comparison with remaining spectral bands independently for the evaluation. Figure 2 illustrates the cross-spectral gender classification using SVM classifier. In applications such as surveillance and security, the image dataset captured in the visible spectrum needs to be compared against a live image captured in varying illumination and unconstrained setting for identification. In cross-spectral matching we aim to match a test image belonging to a particular spectral band against a set of images collected from different spectral band [19]. The detail mathematical details are given as follows:
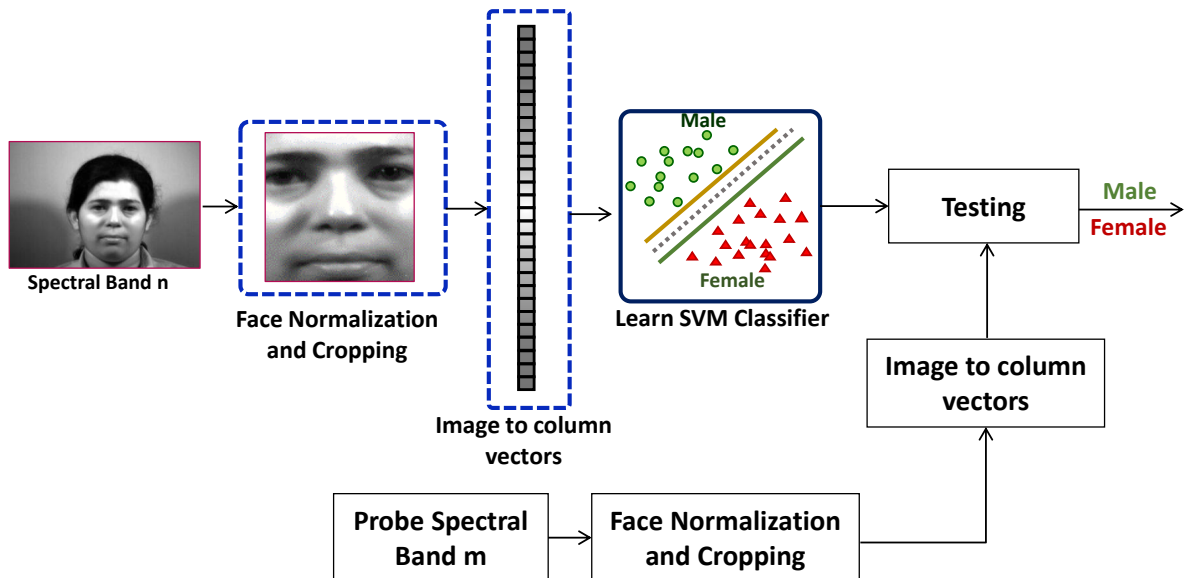

Figure 2. Gender classification based Cross-Spectral Matching and SVM Classifier

Let the set of spectral band facial images be $I_{xn} \in \mathbb{R}^d$ and can be expanded using Equation 1 as follow:

$$I_{xn} = \{I_{x1}, I_{x2}, \ldots, I_{x9}\} \in \mathbb{R}^d \tag{1}$$

where $n = 1, 2, 3, \ldots, 9$ be the nine individual spectral bands and x represents the dimension of column vector ($x = a \times b$ be the spatial dimension of facial image). During training facial images are converted into column vectors before being presented to the SVM as input training data. Each facial image is converted into a column vector of size $(a * b) \times 1$. We then create a training matrix, where each column of the matrix corresponds to a male and female face in the training dataset. Therefore, for M total images in the training dataset, the size of training matrix is $a \times b \times M$.

For gender classification, since it is a two-class problem, we use a linear Support Vector Machine (SVM) classifier [20]. The SVM constructs a hyperplane to separate all the data points of one class from those of other class with the maximum distance between the two.

Let the training set corresponding of N feature vectors µ and their class label x is given by the following representation.

$$\{\mu_n, x_n\}, \forall_n = 1, 2, \ldots N \tag{2}$$

The hyperplane is that separates the two different classes linearly is given by the following equation 3 :

$$y(\mu) = \alpha^T \cdot \theta(\mu) + b \tag{3}$$

where,α are the weights, b is bias, $\theta(\mu)$ is the kernel function, $y(\mu)$ is the gender class label. Thus for a given test image represented by feature vector v and the corresponding class label $g(v)$ is given by

$$g(v) = \begin{cases} 0, & \text{if } v \text{ is male} \\ 1, & \text{if } v \text{ is female} \end{cases} \tag{4}$$

4. Experiments and Results

In this section of the paper, we present the experimental evaluation protocol and related experimental results for cross-spectral gender classification. Specifically, in this work, we train the Support Vector Machine (SVM) model with one spectral band and perform the testing using another spectral band. The purpose of this work is to present the benchmark evaluation results with respect to cross-spectral gender classification. Further, this section presents the quantitative evaluation results based on 145 subject and their corresponding images collected using multi-spectral imaging sensor. To present the classification results, we have evaluated the experiment for 10 fold cross-validation for random selection of training and testing data set, such that the average classification accuracy can be presented.

4.1. Experimental Protocol

This section presents the evaluation protocol employed to perform gender classification of images captured from 145 subjects across the following nine narrow spectral bands: $530nm$, $590nm$, $650nm$, $710nm$, $770nm$, $830nm$, $890nm$, $950nm$ and $1000nm$. The experiment is repeated 10 times using a training and testing dataset that is selected in a random and disjoint manner. The evaluation protocol consists of training set belonging to 40 male and 40 female subjects including their samples resulting in (40 male $\times$ 2 sessions $\times$ 5 samples $\times$ 1 bands) + (40 female $\times$ 2 sessions $\times$ 5 samples $\times$ 1 bands) = 800 spectral band images. The testing set consists of the remaining 47 male and 18 females including their samples, resulting in (47 male $\times$ 2 sessions $\times$ 5 samples $\times$ 1 bands) + (18 female $\times$ 2 sessions $\times$ 5 samples $\times$ 1 bands) = 650 spectral band images. The details related to partition of database under training and testing is summarized in Table 2.

Table 2. Summary describing the number of sample images in training and testing dataset

Training	Male			Female			Total Samples
	Subjects	Sessions	Samples	Subjects	Sessions	Samples	
	40	2	5	40	2	5	800
Testing	Male			Female			Total Samples
	Subjects	Sessions	Samples	Subjects	Sessions	Samples	
	47	2	5	18	2	5	650

4.2. Observation

The purpose of this work is to carry out cross-spectral gender classification using multi-spectral facial database. The idea is to present the extensive benchmark results in the form of average classification accuracy with respect to individual spectral bands when trained with one spectral band and tested with another spectral band. Table 3 present the average classification accuracy obtained after repeating experiment 10 times and Figure 3 present the mean and variance plot for cross-spectral gender classification. Based on the obtained results, we present our major observation as follow:

- The classification results obtained with individual spectral bands presents the reasonable average classification accuracy across all the individual spectral bands.

- When training and testing data corresponding to same spectral band, the highest average classification accuracy of 94.18% is obtained with $890nm$, while the lowest average classification accuracy of 86.5% is obtained with $530nm$ spectrum band. The same can be observed using mean and variance plot shown in Figure 3.

- When the training and testing data corresponding to different spectral band, the highest average classification accuracy of 92.84 (Training band is $890nm$ and testing band is $830nm$) is obtained, while the lowest average classification accuracy of 67.16% (Training band is $1000nm$ and testing band is $530nm$) is obtained, clearly representing the degradation in the performance accuracy due to spectral gab between the training and testing data.

Although the multi-spectral imaging has shown great potential in gender classification with better performance accuracy, the cross-spectral gender classification remains the challenging area and demonstrated using our benchmark results presented in this paper.

Table 3. Average classification accuracy of when the training and testing is performed using two different spectral bands.

Training Spectrum	Testing Spectrum								
	530nm	590nm	650nm	710nm	770nm	830nm	890nm	950nm	1000nm
530nm	86.10	84.03	84.77	82.37	82.71	78.64	80.61	74.72	75.33
590nm	77.61	86.50	90.64	90.77	88.15	87.18	88.96	82.72	84.71
650nm	71.79	84.57	92.82	92.52	91.58	85.76	88.60	78.61	81.41
710nm	63.81	76.26	88.02	92.84	91.93	89.10	91.84	78.60	81.93
770nm	60.17	69.74	90.09	91.87	93.09	85.29	90.00	71.54	71.76
830nm	60.23	70.84	81.31	88.21	85.85	93.09	92.09	86.93	87.69
890nm	56.02	67.38	90.63	91.99	92.41	92.84	94.18	80.55	80.83
950nm	63.69	75.62	78.57	83.17	78.83	90.29	85.79	90.93	90.39
1000nm	67.16	81.00	83.44	85.82	83.43	90.18	91.09	91.63	93.02

(a) 530nm vs Rest of the bands (b) 590nm vs Rest of the bands (c) 650nm vs Rest of the bands

(d) 710nm vs Rest of the bands (e) 770nm vs Rest of the bands (f) 830nm vs Rest of the bands

(g) 890nm vs Rest of the bands (h) 950nm vs Rest of the bands (i) 1000nm vs Rest of the bands
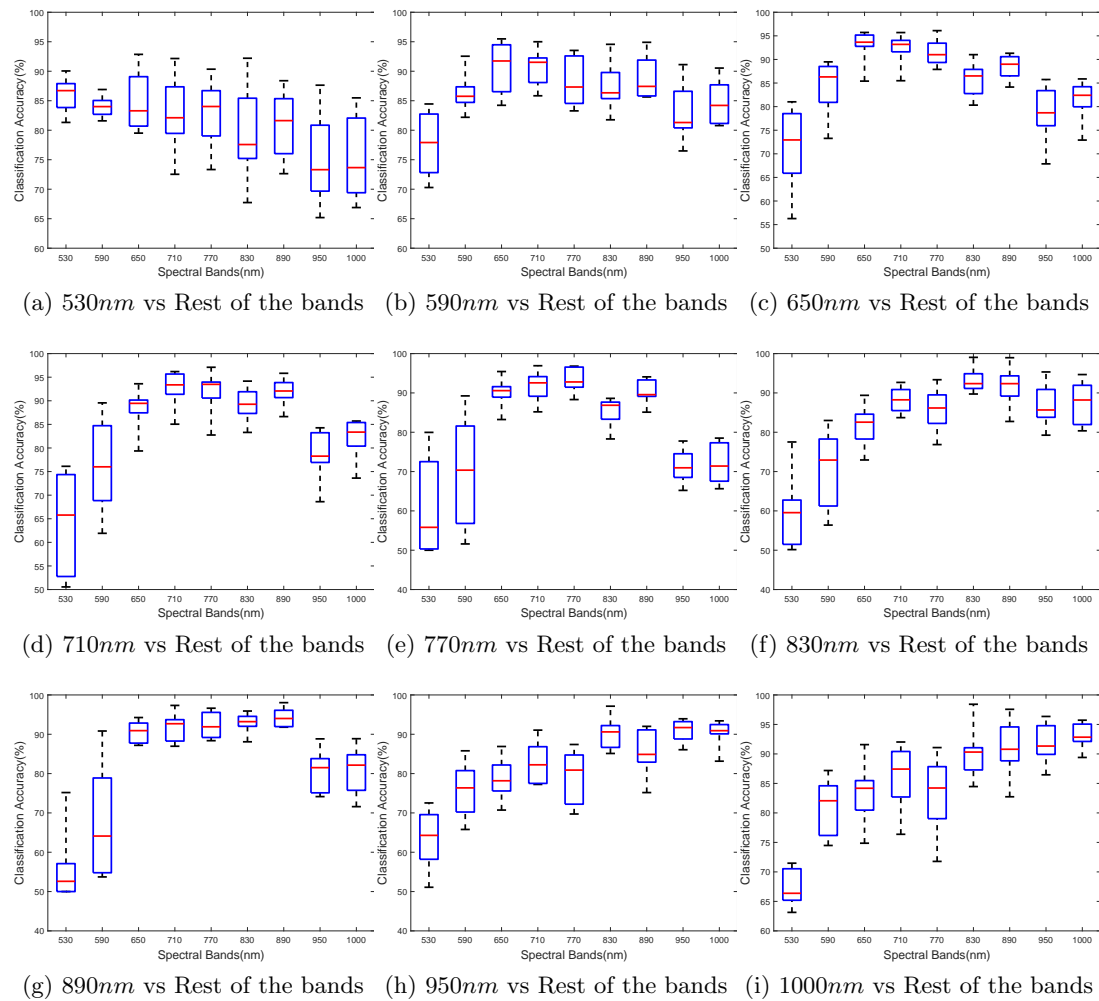
Figure 3. Mean and variance plot illustrating gender classification accuracy for cross-spectral matching.

5. Conclusion

Prediction of gender is getting significant attention in improving the accuracy of biometric authentication system by dividing the training database into two parts in terms of soft labels. Further, spectral imaging is gaining increasing attention due to its potential to collect the spatial and spectral complementary details across the electromagnetic spectrum. Although the performance of individual spectral bands has shown better performance in the recent past when training and testing data belongs to same spectrum bands, while the challenge remains open for cross-spectral gender classification using multi-spectral imaging data. In this paper, we present the cross spectral gender classification based on face database of 145 subjects. We presented the extensive set of benchmark results using 13050 sample images using state-of-the-art Support Vector Machine (SVM) Classifier. The classification results are obtained by using 10 fold cross validation methods in order to randomly select training and testing samples for gender classification. Further, based on our cross-spectral gender classification study, we obtained highest average classification accuracy of 92.84%.

References

[1] Jain A K, Dass S C and Nandakumar K 2004 Soft biometric traits for personal recognition systems *International conference on biometric authentication* (Springer) pp 731–738

[2] Dantcheva A, Elia P and Ross A 2015 *IEEE Transactions on Information Forensics and Security* **11** 441–467

[3] Moeini H and Mozaffari S 2017 *Journal of Visual Communication and Image Representation* **42** 1–13

[4] Bekios-Calfa J, Buenaposada J M and Baumela L 2010 *IEEE Transactions on Pattern Analysis and Machine Intelligence* **33** 858–864

[5] Nicolo F and Schmid N A 2012 *IEEE Transactions on Information Forensics and Security* **7** 1717–1726

[6] Mansanet J, Albiol A and Paredes R 2016 *Pattern Recognition Letters* **70** 80–86

[7] Jain A K, Dass S C and Nandakumar K 2004 Can soft biometric traits assist user recognition? *Biometric technology for human identification* vol 5404 (International Society for Optics and Photonics) pp 561–572

[8] Ross A and Chen C 2011 Can gender be predicted from near-infrared face images? *International Conference Image Analysis and Recognition* (Springer) pp 120–129

[9] Jia S and Cristianini N 2015 *Pattern recognition letters* **58** 35–41

[10] Levi G and Hassner T 2015 Age and gender classification using convolutional neural networks *Proceedings of the IEEE conference on computer vision and pattern recognition workshops* pp 34–42

[11] Hadid A, Ylioinas J, Bengherabi M, Ghahramani M and Taleb-Ahmed A 2015 *Pattern Recognition Letters* **68** 231–238

[12] Ahmad F, Ahmed Z and Najam A 2013 Soft biometric gender classification using face for real time surveillance in cross dataset environment *INMIC* (IEEE) pp 131–135

[13] Narang N and Bourlai T 2016 Gender and ethnicity classification using deep learning in heterogeneous face recognition *2016 International Conference on Biometrics (ICB)* (IEEE) pp 1–8

[14] Chen C and Ross A 2011 Evaluation of gender classification methods on thermal and near-infrared face images *2011 International Joint Conference on Biometrics (IJCB)* (IEEE) pp 1–8

[15] Iglesias-Guitian J A, Aliaga C, Jarabo A and Gutierrez D 2015 A biophysically-based model of the optical properties of skin aging *Computer Graphics Forum* vol 34 (Wiley Online Library) pp 45–55

[16] Vetrekar N, Ramachandra R, Raja K B, Gad R S and Busch C 2017 Robust gender classification using multi-spectral imaging *2017 13th International Conference on Signal-Image Technology Internet-Based Systems (SITIS)* pp 222–228

[17] Vetrekar N, Raghavendra R, Raja K B, Gad R S and Busch C 2017 Extended multi-spectral imaging for gender classification based on image set *Proceedings of the 10th International Conference on Security of Information and Networks* SIN '17 (New York, NY, USA: Association for Computing Machinery) p 125–130 ISBN 9781450353038 URL https://doi.org/10.1145/3136825.3136886

[18] Zhu X and Ramanan D 2012 Face detection, pose estimation, and landmark localization in the wild *2012 IEEE conference on computer vision and pattern recognition* (IEEE) pp 2879–2886

[19] Dawson J, Leffel S, Whitelam C and Bourlai T 2016 Collection of multispectral biometric data for cross-spectral identification applications *Face Recognition Across the Imaging Spectrum* (Springer) pp 21–46

[20] Cristianini N, Shawe-Taylor J *et al.* 2000 *An introduction to support vector machines and other kernel-based learning methods* (Cambridge university press)