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# Gender Recognition Based on Hand Thermal Characteristic

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### Abstract

Automatic gender recognition is one of the frequently solved tasks in computer vision. It is useful for analysing human behaviour, intelligent monitoring or security. In this article, gender is recognized based on multispectral images of the hand. Hand (palm and back) images are obtained in the visible spectrum and thermal spectrum; then a fusion of images is performed. Some studies say that it is possible to distinguish male and female hands by some geometric features of the hand. The aim of this article is to determine whether it is possible to recognize gender by the thermal characteristics of the hand and, at the same time, to find the best architecture for this recognition. The article compares several algorithms that can be used to solve this issue. The convolutional neural network (CNN) AlexNet is used for feature extraction. The support vector machine, linear discriminant, naive Bayes classifier and neural networks were used for subsequent classification. Only CNNs were used for both extraction and subsequent classification. All of these methods lead to high accuracy of gender recognition. However, the most accurate are the convolutional neural networks VGG-16 and VGG-19. The accuracy of gender recognition (test data) is 94.9% for the palm and 89.9% for the back. Experiments in comparative studies have had promising results and shown that multispectral hand images (thermal and visible) can be useful in gender recognition.

### Keywords

Gender recognition; Thermal images; Hand images; Fusion; Convolutional neural network.

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# 1 Introduction

In today's modern world, increased attention is paid to identifying people's demographic characteristics, such as age, gender and ethnicity. These characteristics belong to the field of soft biometrics. Soft biometric traits are physical, behavioural or adhered human characteristics that can be classifiable in predefined human-compliant categories (Dantcheva et al., 2010). These categories are determined and verified by people for distinguishing individuals. Classification of persons into some of these categories involves computer vision. In this article, we will further discuss gender recognition.

Various signs with the help of which gender can be determined are mentioned in the literature. The characteristics with the greatest gender diversity are those in the face and pelvis (Loth and Iscan, 2000). A person can easily classify a man and a woman with a high accuracy of 95% (Bruce et al., 1993). However, in the field of computer vision, this is a very complex task.

Researchers have used the following signs for gender classification: face (Zhou et al., 2019), iris (Tapia et al., 2016), walking (Lu Jet al., 2012), speech (Zhao and Wang, 2019) or hand (Matkowski and Kong, 2020). Our research is focused on hand-based gender recognition. Figure 1 shows the general framework for a hand gender recognition system. There is a hand image on the input. It is further pre-processed. Pre-processing varies according to the methods that are subsequently used for feature extraction. Feature extraction is followed by binary classification.

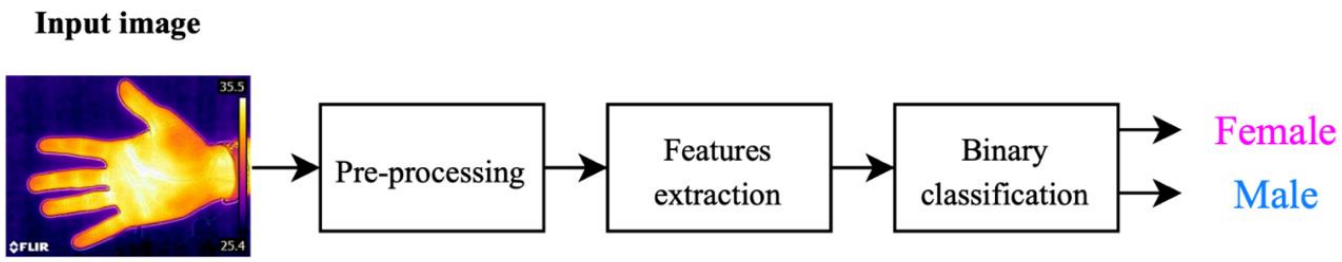


***Figure 1.*** *General framework for hand gender recognition system.*

Gender recognition has a wide range of applications from improving the accuracy of biometric systems to serving gender-based advertising to customers, controlling access to building space, train carriages and changing rooms (Dantcheva et al., 2016; Makinen and Raisamo, 2008). In particular, systems that provide access to buildings (rooms) may have problems with lighting conditions. Whether it is the lack of lighting in the room or outside the entrance, great problems can occur at night.

In this article, we examine the problem of gender recognition from the thermal characteristics of human hands. To our knowledge, this is the first article to try to address the problem of gender classification from thermal hand images. Thermal hand images are obtained using a thermal camera. The thermal camera captures infrared radiation emitted by each object with a temperature higher than absolute zero (-273°C). With this radiation, the surface temperature of the body can be measured. The temperature map of the human skin is a consequence of cellular metabolism and nutrient processing, and it is an individual biometric characteristic. However, thermal characteristics are still very little used in biometric systems. One reason may be the high price of thermal cameras, which has been decreasing recently. At the same time, cameras have appeared that are very small and connect to mobile devices, so thermal cameras are now more affordable. A great advantage is the use of thermal images if the hands are scanned in low light conditions, as thermal imaging does not depend on lighting.

This article will present a recognition system that works with multispectral hand images (thermal and visible images) on the input. Deep learning and machine learning methods are used for extraction and subsequent classification. The aim of this article is to determine whether the thermal characteristics of the hand can be used to determine gender. Section 2 presents related works dealing with hand-based gender recognition and gender recognition using thermal images. Section 3 contains a brief introduction to the multispectral hand image dataset. Section 3 also presents the model of a gender recognition system. Furthermore, the methods used in the system are presented. Experimental results and conclusions are published in the last chapters.

# 2 Related works

This article presents the first gender recognition system known to us that uses the thermal characteristics of the hand. In this section, we give a short overview of related works on gender recognition. The traditional approach to solving the problem of gender recognition is most often found in the literature. This means that specially created feature extractors are most commonly used, followed by distance metrics and classifiers (Afifi, 2019).

Works themed on hand recognition can be found in large numbers. Regarding gender recognition, the number of papers is reduced. Most hand or gender recognition papers work with images in the visible spectrum. If a request for papers that work with thermal spectrum images (Bartuzi et al., 2018; Wang, 2012) is added, the number of papers is very small.

## 2.1 Gender recognition using visible images

Most gender recognition work solves this problem using facial characteristics (Azzopardi, 2016; Cirne and Helio, 2017). Facial gender recognition usually consists of the following steps: facial detection, pre-processing and feature extraction, and binary classification. For example, the LBP algorithm is used for feature extraction and the Real AdaBoost (Yang and Ai, 2007) algorithm is used for binary classification. Another study uses the simple minimum distance algorithm to extract the characters of the dynamic wavelets and LBP algorithms and for subsequent classification (Ullah et al., 2012). These methods have very good results, but they face the following problems. An incorrect classification may occur if a person wears glasses (Li et al., 2018) or wears makeup (Kuehlkamp et al., 2017). Other problems occur when facial images are obtained under low light conditions (Afifi and Abdelhamed, 2017; Afifi et al., 2018).

However, if we use hand images, which are usually obtained under more controlled conditions, we will avoid the above challenges. According to many studies in the fields of anthropology and psychology, there is a great diversity between male and female hands; differences can be seen, for example, in the ratios of the lengths of individual fingers (Brown et al., 2002), or the widths and lengths of hands (Agnihotri et al., 2005). The width of a man's hand is on average 1 cm larger than that of a woman, and the length of a man's hand is 1.5 cm larger than that of a woman (Agnihotri et al., 2005).

The first study to address the problem of gender classification with hand images is from 2008. The system works with the shape of the hand; Zernike moments (ZMs) and Fourier descriptors (FDs) (Amayeh et al., 2008) are used for character extraction. The authors evaluated three different classifiers: minimum distance, k-nearest neighbours (k-NN), and linear discriminatory analysis (LDA). The highest accuracy of 98% was achieved with LDA. In this study, palm scans from 40 people (20 women and 20 men) were used, with a total of 400 images.

Xie et al. (2012) used the skin texture of the back of a human hand to recognize gender. As part of the study, a sensing device was designed for these images. The image database consists of 1,920 images from 80 people (160 hands). The method is based on microtextures (textons). The gender classification reaches an accuracy of 98.65%.

One of the most recent studies on gender recognition based on hand images uses convolutional neural networks (Afifi, 2019). The author created a two-stream neural network using the AlexNet pre-trained network to extract features. He used SVM for subsequent gender classification. The classification reaches 94.2% and 97.3% accuracy for the palm and back of the hand, respectively. Thus, the back of the hand achieves better results in the study. A freely available database was created as part of the study that contained 11,076 images of right and left hands.

Another study uses the latest pre-trained AlexNet, DenseNet, ResNet-50, SqueezeNet, and VGG-16 (Matkowski and Kong, 2020) networks to solve the problem. It works with a freely available database (1,093 images) that were obtained in an uncontrolled environment. The database used was created from hand images available on the Internet (Matkowski et al., 2020).

### 2.2 Gender recognition using thermal images

Most studies use images of characteristic features obtained in the visible spectrum to identify gender. The reasons why thermal images of characteristic features are not used are mentioned in more detail in the Introduction. However, several studies work with thermal facial images (Prihodova and Jech, 2021; Wang et al., 2016) or whole-body images (Nguyen and Park, 2016).

The problem of gender recognition in outdoor areas is solved with the help of an unmanned aerial vehicle (UAV) with a thermal camera (Prihodova and Jech, 2021). In that paper, a model of a controlled UAV flight is designed, during which thermal images of individuals are obtained, and subsequently, the individuals' faces are detected. In the last step, binary classification of detected faces is performed with an accuracy of 82.3% for AlexNet and 81.6% for GoogLeNet.

A hybrid gender recognition method has also been proposed, using the fusion of visible and thermal facial images (Wang et al., 2016). The merging of images is carried out at the level of features and decisions. The results of the study show that fusions at both levels improve gender recognition performance compared to performance using only one type of image (thermal or visible).

Chen and Ross conducted a study to recognize gender from thermal facial images (Chen and Ross, 2011). They first extracted LBP features and then evaluated different gender classifiers in nearby infrared and IR images. Compared to related parts, our contribution is as follows:

a) This is the first article to combine thermal and visible images at the sensor-level to classify gender.
b) This is the first article to use the thermal characteristics of the hand to classify gender.
c) The paper addresses whether the thermal characteristics of the palm or the back of the hand are better for gender recognition.

## 3 Materials and methods

The proposed method to solve the problem of gender recognition is the use of multispectral hand images in the first step. The dataset of thermal and visible hand images was obtained mainly by scanning the hands of employees of the University of Pardubice. Furthermore, machine learning and deep learning methods are used. The method was created and validated in MATLAB and experiments were conducted on an Intel Core i7 at 1.2 GHz. Parallel calculations with 4 cores were used simultaneously.

### 3.1 Data collection

An extensive database containing a total of 9,200 hand images from 46 subjects (23 men and 23 women) was used for the experiments. It is a database of thermal images and visible images. A pair of thermal and visible images were obtained at the same time using two cameras (visible and thermal). The size of each frame is 320x240 pixels.

Each subject was scanned a total of 50 times in at least two sessions, separated by at least 7 days. This is because the temperature of the hand can change over time. At the same time, during scanning, subjects accidentally spread their fingers, so that more diverse shapes of individual hands are obtained. The right hand was scanned, always the palm and back of the hand. The age of the scanned persons varies, ranging from 15 to 75 years. To create a high-quality dataset, it is necessary to determine the conditions for capturing images of the hand:

- Each subject was asked to randomly extend the fingers of the right hand during shooting and to change the position of the fingers during shooting. The hand was photographed from both sides (dorsal and palm). The distance of the hand from the camera was always 30 cm.
- The scanning process was repeated at least twice on different days and times of the day to take into account variations that may occur over time.
- Hand shots were taken no earlier than 30 minutes after the last physical exertion.
- The people did not have symptoms of an infectious disease, such as fever.
- The scanning took place indoors, under constant conditions with a room temperature of 21°C – 23°C, which are temperatures that ensure thermal comfort of average people (Fabbri, 2015); the person being sensed was acclimatized in the room. The lighting was not constant.

## 3.2 Methods

The aim of this study is to find out whether it is possible to recognize gender according to the thermal characteristics of the hand, and at the same time, to find the best architecture for this recognition. For this purpose, we selected sensor-level fusion (thermal and visible image) several methods of machine learning (classifiers) and deep learning (CNN architectures).

Thermal characteristics have a great advantage under low-light conditions, because light conditions do not play a role in capturing them. Furthermore, it is very difficult to steal or imitate these characteristics. The hand was chosen for gender recognition for practical reasons. This is the part of the body that requires the scanned person's cooperation. This is a positive feature nowadays, when invasions of privacy are dealt with very often.

Thanks to the use of the FLIR camera, which is a combination of a thermal and visible camera, it is possible to perform a fusion at the sensor-level. The sensor-level fusion results in multi-spectre dynamic images (MSX). Figure 2 shows examples of MSX images.

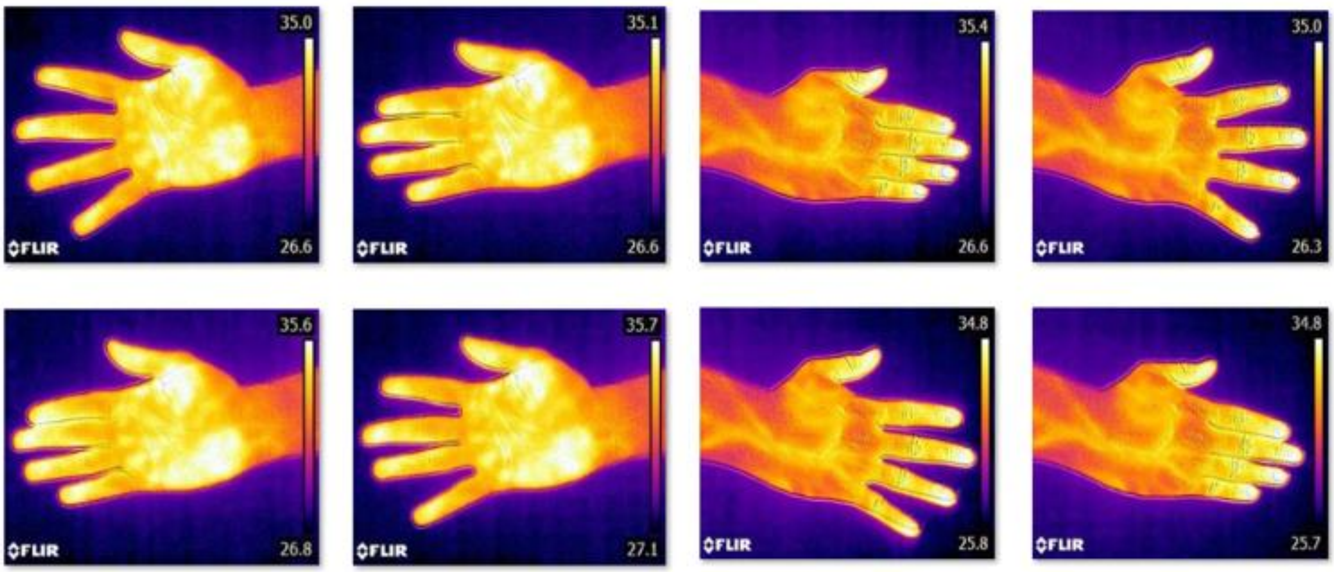


***Figure 2.*** *Example multi-spectre dynamic images from database.*

MSX is not just a combination of a thermal and visible image. Useful visible details, such as lines and edges, are captured in the image, which are then superposed directly on the thermal image (FLIR, 2019). No information is lost from the thermal image. Figure 3 shows one hand image in different spectrums: thermal image, visible image, MSX image.

Gender recognition can be considered a binary classification issue. This can be solved with a classic or a modern approach.


***Figure 3.*** *Example thermal image, visible image, MSX image.*

### 3.2.1 AlexNet and Machine learning

The aim of the proposed method is to solve the above classification problem using CNN as a feature extractor and machine learning methods for classification. For feature extraction, we used the AlexNet convolutional neural network with initial pre-trained network values. In the first step, MSX hand images were resampled using the closest-neighbour interpolation method to a size of 227x227x3, which corresponds to the required AlexNet input size.

The image database was divided into training data (70%) and test data (30%). Thus, the training data are images from 16 men and 16 women, and the test data are images from 7 men and 7 women. Care was taken to ensure that images from the same person were not included concurrently in both the training and the test data. The database divided in this way was used for all the experiments.

This was followed by feature extraction using AlexNet. The network creates a hierarchical representation of the input images. Deeper layers contain higher-level features created using lower-level features of previous layers. Since we wanted to get higher-level features from both training and test images, we took advantage of the extraction of features from the 'fc7' layer.

After feature extraction, several types of support vector machine (SVM), linear discriminant, naive Bayes classifier and neural network classifiers were tested and optimized. The principal component analysis (PCA) method was also tested, which reduces the number of features extracted so as not to cause overfitting. At the same time, classifier training is shorter when using this method.

### 3.2.2 CNNs

In this part of the article, the above-mentioned classification problem is solved using deep learning methods. We chose to use convolutional neural networks. At the beginning of the training, we used the initial values of the pre-trained AlexNet, GoogLeNet, VGG-16 (Figure 4), and VGG-19 networks.

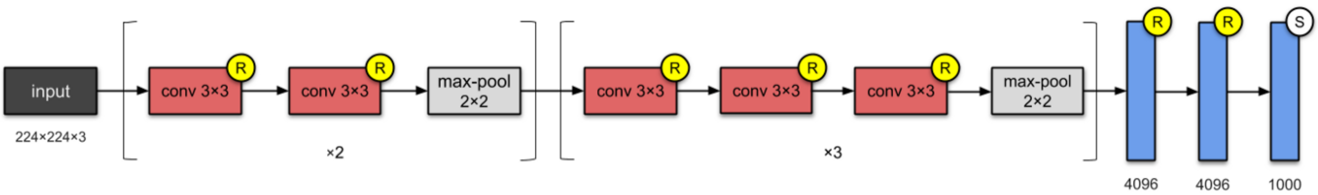


***Figure 4.*** *VGG-16 convolutional neural network architecture. Source: (Raimi, 2019).*

For convolutional neural networks, targeted image pre-processing is not required, except for a change in input size. Each neural network has different input size requirements (227x227x3 for AlexNet and

224x224x3 for GoogLeNet, VGG-16 and VGG 19). Therefore, the MSX hand images were resampled using the nearest neighbour interpolation method according to CNN input size requirements. The image database used for these experiments is divided in the same way as for the AlexNet and classifier experiments. After resizing the MSX images, training of the selected CNNs followed. 70% of the data (training data) were used for the training.

The widely used backpropagation algorithm for gradient computing was used to learn neural networks. Furthermore, the stochastic gradient descent optimization algorithm was used to minimize errors. Due to the hardware used to implement the system, the batch size was set to 32. The number of epochs was set at 16 for AlexNet and GoogLeNet and only 7 for VGG-16 and VGG-19. A large number of scenarios led to network parameters that provided a learning error value kept below the required limit. One of the most important parameters, learning rate (0.0001) was also optimized. The proposed model was subsequently tested using test data. In the last step, the accuracy of the system was determined, and a comparison of individual methods was performed.

# 4 Results

In this work, we collected a new dataset of thermal and visible images, mostly from the University of Pardubice. MSX images were created from this dataset. The MSX images were then pre-processed so that all were of the required size. This study compared several CNN architectures: AlexNet, GoogLeNet, VGG-16 and VGG 19. Common classifiers using extracted features from AlexNet were also tested.

Figure 5 shows the visualizations of the activations of the first convolution layer of the trained AlexNet network. These visualizations show what features the network has learned on both sides of the hand (palm and back). These are mainly the contours of the hand, but also the body temperature of the hand.

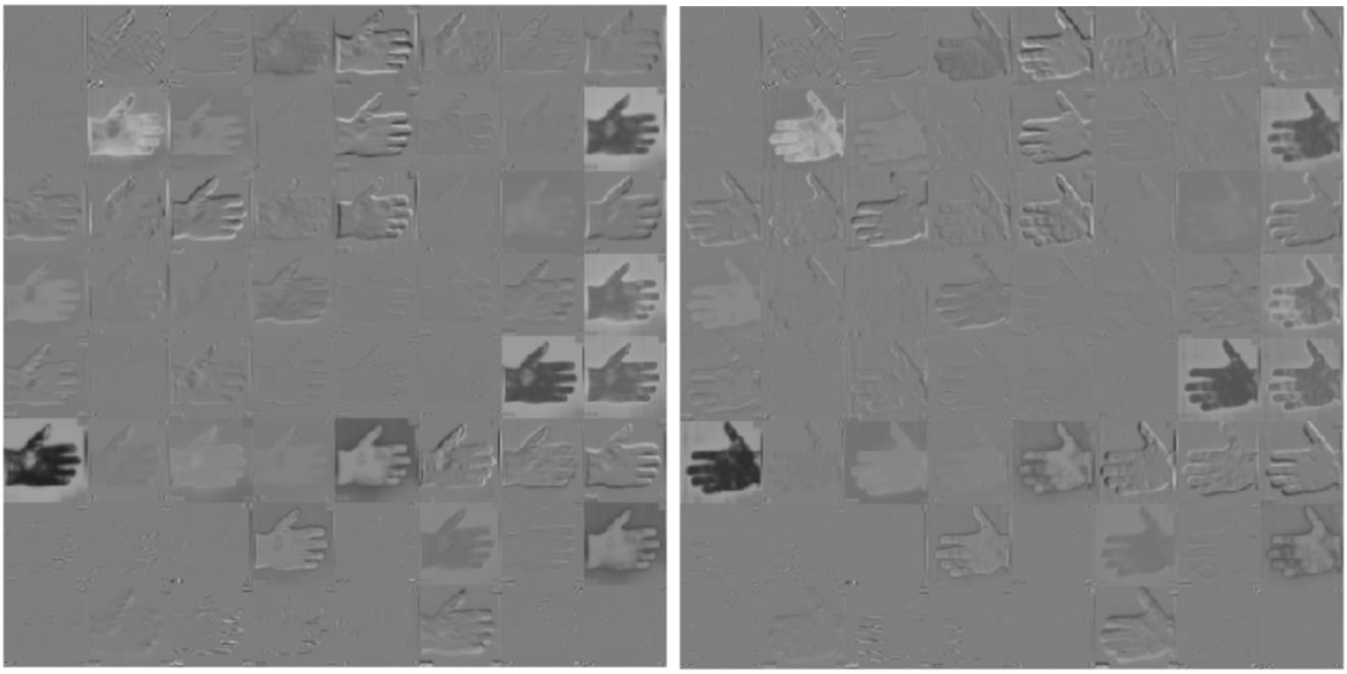

***Figure 5.*** *Confusion matrix for VGG-19, VGG-16, AlexNet + SVM Gaussian, AlexNet + linear discriminant.*

The results were compared on the basis of metric accuracy (Equation 1):

$$ACC = \frac{TW + TM}{T + N} = \frac{TW + TM}{TW + TM + FW + FM} \quad (1)$$

where T stands for true classified persons, and F for false classified persons; W stands for woman and M for man.

True classified woman (TW): the prediction is a woman and the image is of a woman's hand.

True classified man (TM): the prediction is a man and the image is of a man's hand.

False classified woman (FW): the prediction is a woman and the image is of a man's hand.

False classified man (FM): the prediction is a man and the image is of a woman's hand.

Table 1 shows a comparison of the classification accuracy obtained when testing methods.

***Table 1.*** *Gender recognition results using our dataset accuracy test.*

| **Method** | **Accuracy** | |
|---|---|---|
| **Machine learning** | **Dorsal** | **Palm** |
| AlexNet + SVM (Gaussian) | **87.1%** | 87.3% |
| AlexNet + linear discriminant | 85.9% | **89.7%** |
| AlexNet + SVM (linear) | 85.6% | 88.3% |
| AlexNet + wide neural network | 85.1% | 86.3% |
| Alex Net + naive Bayes (Gaussian) | 84.4% | 88.3% |
| AlexNet + SVM (cubic) + PCA | 84.1% | 83.0% |
| **CNNs** | | |
| AlexNet | 85.6% | 92.7% |
| GoogLeNet | 82.6% | 90.1% |
| VGG-16 | **89.9%** | 93.0% |
| VGG-19 | 86.1% | **94.9%** |

SVM classifiers with different kernels (linear and Gaussian), linear discriminant, wide neural network and naive Bayes with a Gaussian kernel were tested. The SVM with kernel cubic classifier was also tested, which extracted features on the input, which were reduced by PCA. Furthermore, the convolutional neural networks AlexNet, GoogLeNet, VGG-16 and VGG-19 were tested.

Generally, better results are achieved with images of the palm, regardless of the classifier or neural network used. The best results are achieved by VGG-16 for the back of the hand (89.9%) and VGG-19 for the palm (94.9%). However, these methods have very long training times compared to machine learning methods, as can be seen in Table 2.

***Table 2.*** *Training time in seconds for proposed methods.*

| Method | Training time | |
|---|---|---|
| **Machine learning** | **Dorsal** | **Palm** |
| AlexNet + SVM (Gaussian) | 350.43 | 421.05 |
| AlexNet + linear discriminant | **90.226** | **101.52** |
| AlexNet + SVM (linear) | 151.62 | 190.31 |
| AlexNet + wide neural network | 1,940.7 | 2,044.1 |
| Alex Net + naive Bayes (Gaussian) | 178.35 | 223.85 |
| AlexNet + SVM (cubic) + PCA | 264.06 | 216.85 |
| **CNNs** | Dorsal | Palm |
| AlexNet | 2,455 | 2,451 |
| GoogLeNet | 6,916 | 7,911 |
| VGG-16 | 16,161 | 16,808 |
| VGG-19 | 20,086 | 19,919 |

The differences between the training times of machine learning methods and convolutional neural networks are great, and the training of machine learning methods is much shorter. In order to better evaluate the best-performing models from both approaches, we created a confusion matrix from the test data, working with absolute frequencies. There were a total of 700 test data (350 men and 350 women). From the confusion matrix in Figure 6, it is clear that neural networks, as well as the combination of AlexNet + classifiers, have a greater problem with the classification of women, who are more often misclassified than vice versa. The neural networks AlexNet + linear discriminant make very few mistakes in classifying men compared to AlexNet + SVM. It can be seen from the confusion matrix, as well as from Table 1, that better results were obtained with palm images.

Absolute frequencies were converted to relative frequencies to obtain the true positive rates (TPR) and false negative rates (FNR). These rates can be found in Table 3.

***Table 3.*** *True positive rates and false negative rates.*

| Method (dorsal/palm) | | TPR | FNR |
|---|---|---|---|
| AlexNet + SVM (Gaussian) – dorsal | Man | 91.4% | 8.6% |
| | Woman | 82.9% | 17.1% |
| AlexNet + linear discriminant – palm | Man | 99.7% | 0.3% |
| | Woman | 79.7% | 20.3% |
| VGG-16 – dorsal | Man | 98.3% | 1.7% |
| | Woman | 18.6% | 81.4% |
| VGG-19 – palm | Man | 99.7% | 0.3% |
| | Woman | 10.0% | 90.0% |

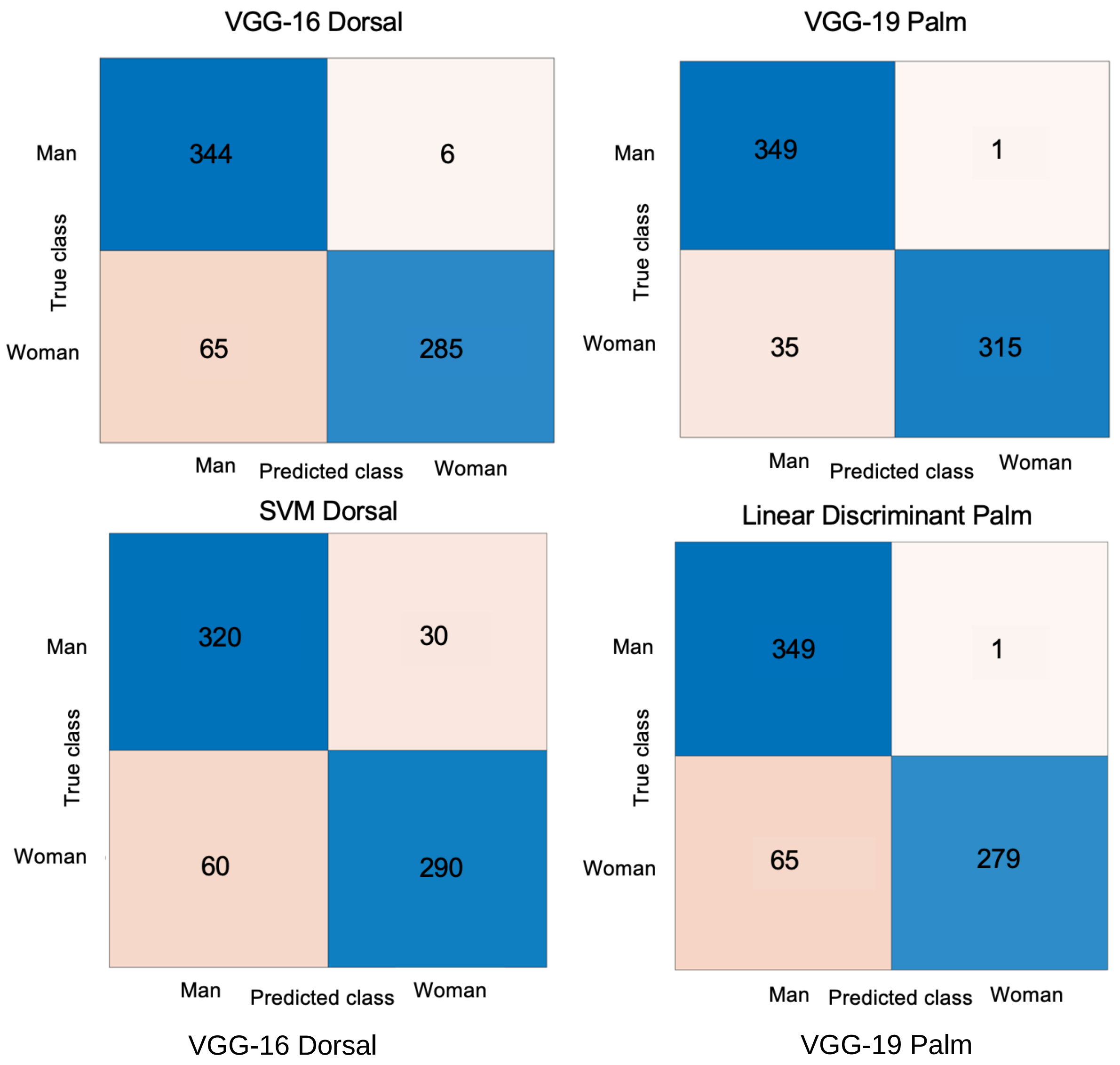


***Figure 6.*** *Confusion matrix for VGG-19, VGG-16, AlexNet + SVM Gaussian, AlexNet + linear discriminant.*

## 5 Discussion

A database of 4,600 MSX images was used for learning in selected machine learning and CNNs methods. It is a relatively large database of hand images with thermal characteristics. The database has images taken in two scans from 23 men and 23 women. Using a larger training database can help further verify our results. For verification, it would be a good idea to create a new database of thermal hand images with more time variability than just one week.

Another option to expand the research is the use of a higher-resolution thermal camera to obtain better images on the input, which could affect the overall accuracy of the system.

In the last two years, the world has been faced with a COVID-19 pandemic. It is a viral disease, the primary symptom of which is increased body temperature. For this reason, too, it has recently become desirable to recognize people with fever, for example, when entering buildings. Based on these facts, we propose a possible extension of research work to the task of recognizing people with elevated body temperature.

No experiments have been conducted in the research that intentionally lower or raise the hand temperature to "cheat" the system (for example, taking images after holding a cup of coffee or cooling the hand in cold water), which could be a new research direction. I decided not to publish the database of



Woman

hand images created by me, mainly because some of the people did not consent to the publication of anonymized data.

## 6 Conclusions

In this work, we tested a set of state-of-the-art methods on a new set of MSX hand images for gender recognition. The MSX images were created by fusing thermal and visible images. No information from the thermal image was lost during this fusion.

We used AlexNet to extract features and then tested various classifiers (SVM, linear discriminant, neural network and naive Bayes. We achieved the best results with SVM with a Gaussian kernel (87.1%) for the back of the hand and linear discriminant (89.7%) for the palm.

A reduction in the number of features extracted from AlexNet using PCA was also tested. This reduction prevents overfitting and at the same time reduces the time required for the method. The SVM classifier with a cubic kernel achieved very good results with such reduced features.

Neural networks were also tested, which performed better than AlexNet + classifier. Of all the methods tested, VGG-16 (89.9%) for the back of the hand and VGG-19 (94.9%) for palm have the best neural network results.

Extensive experiments have shown that the thermal characteristics contained in MSX images have features that could help address the problem of gender recognition. Experiments have also shown that MSX images of the palm are better than those of the back of the hand.

## Additional Information and Declarations

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**Conflict of Interests:** The author declares no conflict of interest.

**Author Contributions:** The author confirms being the sole contributor of this work.

**Data Availability:** The data that support the findings of this study are available from the corresponding author.

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