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Thermal-based gender recognition using drones: advancing biometric recognition in challenging outdoor environments

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Abstract

While biometric recognition typically uses features such as face, fingerprint, and iris to identify individuals, this study focuses on utilising specific characteristics to identify gender. The aim of this article is to propose a procedure for gender recognition under specific conditions. The specific condition addressed is outdoor area monitoring, which presents challenges such as varying lighting conditions and limited camera placement options. To tackle this, a proposed procedure utilises thermal images captured by the drone equipped with a thermal camera. The advantage of thermal images is their independence from ambient light conditions. The captured images are resized and processed using convolutional neural networks (CNNs) (AlexNet, VGG-16, VGG-19) for feature extraction and binary classification. A freely available database of thermal face images is used for training the CNNs, while a own created dataset of thermal images obtained by the drone is used for testing. The findings indicate that the optimised CNNs achieve classification accuracies of 82.4% (VGG-16), 82.9% (AlexNet), and 85.5% (VGG-19). The original contribution of this study lies in demonstrating the suitability of face thermal images obtained through drones for gender recognition purposes.

Key words: drone, gender recognition, thermal image, convolutional neural networks

Introduction

Gender recognition is a problem in computer vision and machine learning; solving it is a long-term interest. We most often encounter gender recognition based on the face, which can also be used to identify people, determine their ethnic origin, or estimate age (Loth and Iscan 2000; Carletti et al. 2020). In recent years, research has focused on new methods and techniques that would enable more accurate and reliable gender recognition. One possible way is to use face thermal images. This approach brings several advantages over traditional methods that use regular RGB images. The main advantage of thermal images is their independence from lighting conditions, which means they can provide more reliable information even in poor lighting conditions, such as darkness, intense lighting, or shading.

The aim of this article is to propose a procedure for gender recognition under specific conditions. A specific condition is the monitoring of the outdoor space. When monitoring outdoor spaces, we may encounter poor light conditions and even darkness. The problem can also arise with many access routes to the outdoor area and placing fixed thermal cameras at all entrances is either very expensive or even impossible. One of the possible ways to collect data in outdoor spaces is using drones (thermal camera carriers). These have been improved in recent years of development in terms of technical properties, autonomy, minimisation, and controllability.

The contribution of this paper is the presentation of a procedure which includes a convolutional neural network (CNN)-based model for classification in the field of gender recognition. Face thermal images, which are obtained using a drone to solve specific conditions, are classified. It can provide more reliable and accurate results compared to traditional methods. The procedure could contribute to progress in gender recognition and provide valuable information for applications such as security systems, personalised marketing, or crowd analysis.

In the following sections of the article, we will present the current state of the problem the proposed methodology for gender recognition, analyse, and discuss the results of our experiments and compare them with existing approaches.

Current state in the research area

In the literature, we encounter several different features that can be used to identify gender. However, the features with the most significant sexual diversity are the features of the face (jaw, chin) and pelvis (Loth and Iscan 2000). When recognising gender, we encounter two approaches (traditional and modern). However, both take place in the

Fig. 1. Face images (subject is author)—different parts of the electromagnetic spectrum: visible and infrared light.

following steps: face detection, pre-processing, features extraction, and binary classification.

In the traditional approach, an expert constructs special extractors tailored to the given biometric characteristics. This method can be tedious, especially when the input vector is dimensional. Currently, the second approach to feature extraction is on the rise. In the second approach, biometric features are obtained using learning from data; this is how, e.g., neural networks are learned.

Gao and Ai (2009) use AMS for features extraction, and Adaboost is used for subsequent classification. The system works with visible face images and its accuracy is 92.9%. Shan (2012) uses the local binary pattern (LBP) algorithm to extract features, and the SVM classifier is used for subsequent classification. The system also has visible face images at the input and its accuracy is 94.8%. In addition to the traditional approach, deep learning methods have recently been promoted. In the field of person recognition, these are mainly CNNs.

In a modern approach, CNNs automatically extract features; the functions extracted in this way are used in the last layers of CNN for classification. Rafique (2019) used CNNs to recognise gender and age from face images.

All the studies mentioned above work with visible face images. However, the system with visible images hits its limits, especially in poor light conditions (Afifi et al. 2018; Afifi and Abdelrahman 2019). One way to solve this problem is to use thermal face images. Currently, thermal images are obtained with the help of a thermal camera, while the detector in the thermal camera detects the intensity of infrared radiation. Since the intensity of infrared radiation directly depends on the body's surface temperature, the thermal camera can calculate and display the temperature. The body's surface temperature is displayed on a thermal image (thermogram). Figure 1 shows face images acquired in different parts of the electromagnetic spectrum (infrared light, visible light).

Body surface temperature information can also be used as another biometric characteristic. Since the temperature map of our skin is a consequence of cellular metabolism, the processing of nutrients (carbohydrates, lipids, and proteins), it is therefore an individual anatomical characteristic (Kopaczka et al. 2017). Bhattacharjee et al. (2012) uses two techniques for feature extraction: the first is Haar Wavelet Transform, and the second is LBP. As a classifier, a back propagation feed forward neural network or a minimum distance classifier is used in this paper. Jalil and Reda (2022) used the CNN deep ResNet for gender recognition. It is one of the few works that uses CNNs in the field of thermal imaging. There are also very few publicly available thermal image databases. However, one fully annotated database exists; examples from this FATFD database are in Fig. 2 (Kopaczka et al. 2019).

As part of using drones for data acquisition, there is an interesting possibility of using drones equipped with thermal cameras. These drones are becoming a suitable means of obtaining thermal images of various objects (Tkáč and Mésároš 2019). When collecting data using drones, it is necessary to follow the national legal regulations that deal with flying with drones. In Czechia, national legislation is given by CAA (ÚCL 2023). Furthermore, as of 1 January 2021, legislation in the EU unifies the rules for flying with drones in all EU countries (EASA, 2021). The new EU legislation has a category for flying regarding the associated risks; it is named "specific". These risks cover all possible accidents and must have preventive measures to deal with them.

With regard to the acquisition data of people, there is an existing risk of drones falling, which needs to be solved by robust technology. In the specific category, the permission of the competent authority is required before the operation takes place, considering the mitigation measures identified in the operational risk assessment. The category Specific allows more complicated flights over people and populated areas. The category Open A2 can be used for flying with big and heavy drones close to people and buildings, but this category has limitations. The optimal situation is when a pilot is the owner of both Specific and Open A2 category licences. When using drones as a source of thermal images of people in a larger area, it is necessary to thoroughly cover the monitored area, which can be achieved by the planned flight.

Video, time-lapse, or waypoints (points of stops where an image can be photographed) represent typical outputs of the planned flight. During a planned flight, a specific setting of the sensor is necessary, especially its scanning angle (its angle of capturing images between the object and the sensor to the plane), which is necessary to ensure the quality of the captured images.

Fig. 2. Examples of thermal images of men and women from the fully annotated thermal face database (Kopaczka et al. 2019).

Materials, methods, and proposed procedure

Data and material

In this study, the following data and materials were used to create a gender recognition procedure based on drone face thermal images:

Drone: A DJI Mavic 2 DUAL Enterprise drone with integrated thermal sensor (Fig. 3) was used for data collection. Its thermal sensor has resolution of 160 × 120 pixels, spectral band 800–1400 nm, and combined output image has resolution 640 × 480 pixels.

Hardware and software: A CNN (AlexNet, VGG-16, VGG-19)-based gender recognition system was developed and validated in MATLAB, and experiments were performed on an Intel Core i7 at 1.2 GHz.

Database: There is only one database of face images in the thermal spectrum of the available and suitable database for training data for training CNNs (Kopaczka et al. 2019). The FATFD contains 2500 images. Thermal images of 74 men and 14 women are included.

Dataset: Thermal images from a drone were used as testing data. The own collected dataset (OCD) itself contains 252 thermal images. The thermal images represent eight men and six women. This OCD dataset was used to test CNNs.

The FATFD database and the OCD dataset were created or carefully selected considering different lighting conditions and different genders to ensure representativeness of the data.

Methods

A list of methods used to create a gender recognition procedure based on face thermal images obtained from a drone follows.

Planned flight: The planned flight is a technique of collecting data obtained by a drone. This technique provides cost-effective flight and proves that output image data are consistent with minimal redundancy.

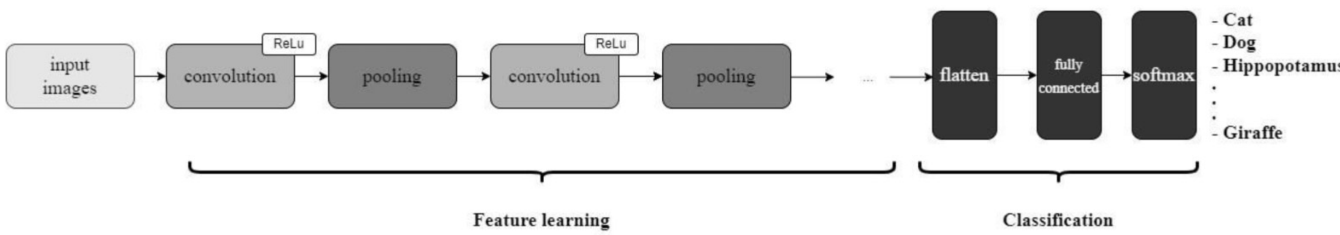
Flight planning is the process of preparing all aspects of a planned flight before takeoff. It involves a comprehensive assessment of various factors to ensure the safe and efficient execution of the flight (Bashioum et al. 1965). Flight planning is crucial for both manned and unmanned aerial vehicles (such as drones) and is a standard practice in aviation. The main factors are fuel calculation and compliance with air traffic control. A few approaches to flight planning exist: as waypoint route flight, polygon flight, and more (Ruscio et al. 2016). Polygon planned flight is the most relevant for scanning area, providing optimal covering by obtained image data with minimal redundancy. For the best quality of obtained image data, input parameters for planned flight, such as image overlap of 80% and more (Tu et al. 2020) and ground sample distance (GSD), are required. GSD represents the size of one pixel on the ground and is related to flight altitude and the possibilities of a camera sensor.

CNNs: Recently, a significant focus has been on CNNs. They are used to solve classification problems.

A CNN consists of an input layer and hidden layers with different functions. The first hidden layer is a convolutional layer with an activation function; the Relu activation function is often used. The first convolutional layer extracts features that serve to detect colours and edges. Deeper convolutional layers detect more complex features than the first convolutional layers. The second hidden layer is the pooling layer; this layer shrinks the image. Further convolutional layers with an activation function follow, which are again followed by a pooling layer. At the end of the CNN are fully connected layers with the Softmax activation function used for classification. A typical CNN architecture is shown in Fig. 4 (MatlabWorks 2021).

Fig. 3. DJI Mavic 2 DUAL Enterprise drone.

Fig. 4. Typical convolutional neural network architecture.



In 2012, Alexandr Krizhevsky won the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) with the AlexNet CNN, this helped popularise this kind of neural network. The original AlexNet architecture had two parallel streams of image processing. The dual-stream network was designed to use two GPUs (graphics processors) working together to create a training model with higher speed and memory sharing. Nowadays, a single-stream network is already used, which is shown in Fig. 5. AlexNet has 60 million parameters in eight layers—five convolutional and three fully connected (Krizhevsky et al. 2017). The AlexNet network and its variations have been used in the field of biometrics, for example, for real-time face recognition (Omotosho et al. 2021) or ear recognition (Almisreb et al. 2018). Furthermore, the AlexNet algorithm was used to recognise fish species (Ju and Xue 2020).

The VGG-16 network, designed by Karen Simonyan and Andrew Zisserman in 2014 at the University of Oxford, England, placed a close second in the ILSVRC competition to GoogLeNet (Simonyan and Zisserman 2014). VGG-16 has 13 convolutional layers and 3 fully connected layers, and like AlexNet, the ReLu activation function is used in its architecture (Fig. 6). It consists of 138 million parameters and takes about 500 MB of storage space. VGG networks have been designed in various configurations ranging in size between 11 and 19 layers, the most powerful being networks with 16 or more layers.

A development trend can be seen in these networks—increasing the depth of the networks. It is the most direct way to improve the performance of deep neural networks (Szegedy et al. 2015). It also illustrated another important innovation that has become standard in newer architectures of CNNs. An important innovation of VGG is that these networks have simultaneously reduced filter sizes as the network depth has increased. Reduced filter size requires greater depth. This is because a small filter can only capture a small area of the image (3×3 small size filter is the smallest filter that can capture the impression of right, left, bottom, top, or centre) unless the network is deep.

The VGG network and its variations have been used in the field of biometrics, for example, to recognise facial expressions (Parihar et al. 2021). Furthermore, the VGG algorithm was used to recognise traffic signs or vegetables (Li et al. 2020).

Proposed procedure

A description of the proposed gender recognition procedure based on thermal face images obtained from a drone follows (see Fig. 7).

Drone setup: First, it was necessary to set up the drone for data collection properly. This included checking and calibrating the temperature sensor and setting the flight parameters. The thermal image sensor is able to get a thermal range from −10 to 140 °C (high gain). Because the human body's temperature will be measured, the thermal sensor was set to a fixed temperature range from 30 to 45 °C as minimal and maximum sensing values. Also, this range covers colder or hot-

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Fig. 5. Architecture of the AlexNet convolutional neural network.

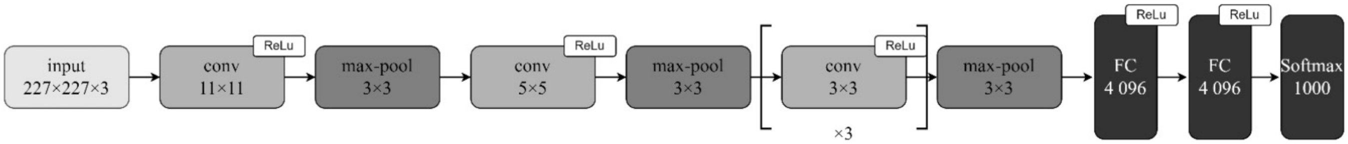


Fig. 6. Architecture of the VGG-16 convolutional neural network.

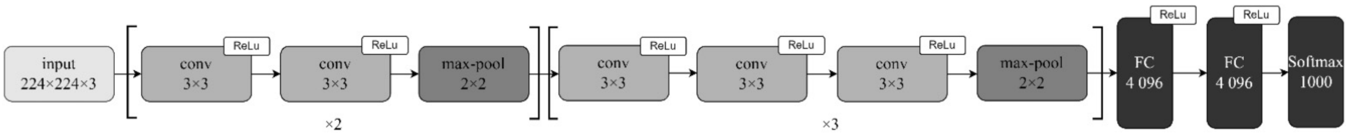
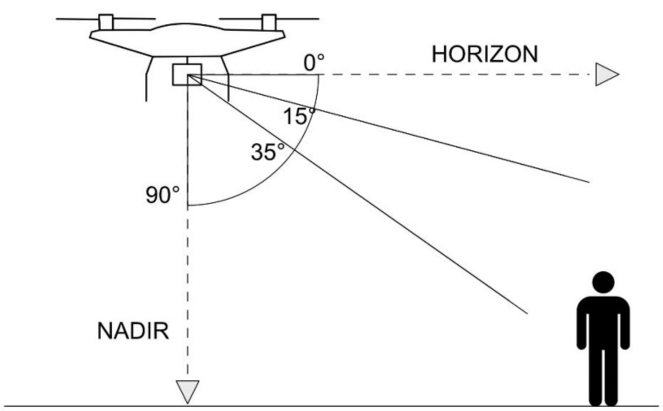


Fig. 7. Proposed procedure.

Fig. 8. Experimental phase—recommended shooting angle.



ter temperatures of a body's surface during different weather seasons.

The investigated flight parameters were the scanning angle and the flight level. The parameters optimal setting was sought experimentally to ensure the best image quality and comply with the legislation. During the experimental phase, there were tested settings of capturing angle from 10° to 50°, where steps were changed by 5°. This range is relevant to shooting objects in a way of a flight. Moreover, photographing persons from different sides was tested. The result of the experimental phase was that shooting angle must be between 15° and 35° against horizontal sensing, where 90° is perpendicular shooting, see Fig. 8. The shooting angle changes with the flight level of the carrier. The optimal capturing angle was at an angle of 25°, flight level 5 m, and distance from objects 5 m—according to legislation (flight in tripod mode). There is one exception: if people are involved in the flight, then it is possible to fly over people. The optimal angle of captured images respective faces is given by visual comparison of images taken by different angles. Low altitude flight was due to thermal sensor to provide good quality of thermal images. With this low-altitude flight, many risks can exist, from hardware malfunction to social aspects of near flight of drone.

Planned flight itself: A planned flight of the drone was carried out to collect thermal images of faces. Before the flight, the target areas were determined, in which the people were focused for sensing. The planned flight ensured that the drone sufficiently covered the monitored area and allowed the necessary data to be obtained for gender analysis. The planned flight (Fig. 9) was set by rules for covering images inside planned flight and also by setting of taking images of faces (see Table 1).

Data acquisition and raw dataset creation: The output images from a planned flight, raw images, contain much information, and some of it is unnecessary for this purpose. The only important object from the images is the face, which must be identified. Ren et al. (2017) algorithm was used for face detection. Next, the detected faces were cropped, and a testing OCD dataset was created.

Editing dataset and database: FATFD database was used for training CNNs, and created OCD dataset was used for testing CNNs. For our study, it was necessary to divide images into two categories (male and female). This process was done manually. The FATFD database and OCD dataset are not balanced by the number of class representations (male and female). The FATFD database contains 424 female images and 2483 male images. The OCD dataset contains 109 female images and 143 male images. For this reason, it was necessary to balance the classes using image transformations. Mirroring, rotation, and magnification were used as image transformations.

Data pre-processing: Thermal face images from FATFD database and created OCD dataset were resampled into the

Fig. 9. Planned flight with settings in software tool Dronelink (Dronelink, n.d.).

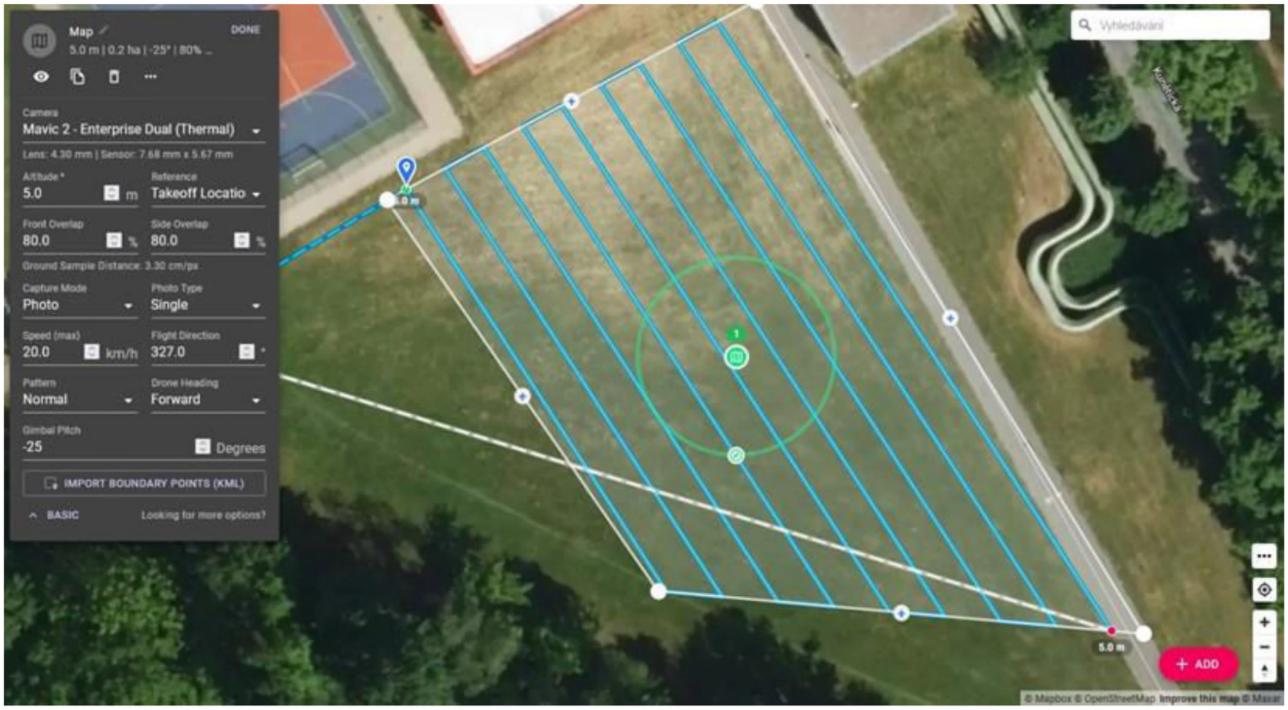


Table 1. Parameters of planned flight.

Parameter of planned flight	Value
SW for planning	Dronelink (v 4.9.0)
Altitude	5 m (above ground)
Front overlap	80%
Side overlap	80%
Speed	5.56 m/s
Shooting angle	25°

required size (227 × 227 × 3 or 224 × 224 × 3) of input data to neural networks. For resampling, the nearest neighbour interpolation method was used. Figure 10 shows examples of already pre-processing images obtained using a drone. The examinee gave permission for the images to be published, as it is not possible to recognise who it is in the images.

Feature extraction and classification: The feature extraction and subsequent classification were performed by CNNs. The most commonly used CNNs AlexNet, VGG-16, and VGG-19 were gradually tested in the proposed procedure (Karpathy et al. 2020).

After image pre-processing, CNNs were trained on training data (FATFD database). A backpropagation algorithm, which uses stochastic gradient descent to minimise errors, was used to train all CNNs. Due to the computing technology on which the implementation was performed and the size of the FATFD database, the batch size was set to 128. The epoch was set to 7. Finding network parameters that provided a learning error value that remained below the required limit results from many different test scenarios. The Learning Rate parameter (0.0001) has been optimised.

Then, the selected CNNs were verified using test data (OCD dataset—thermal images from drone), and the system's accuracy was determined. Finally, a comparison and comparison with existing approaches was made.

Evaluation of results: The results of gender recognition based on thermal face images were evaluated using classification accuracy (Formula 1). Furthermore, the results were compared with existing approaches to gender recognition from face images (Table 1).

$$\text{Acc} = \frac{\text{TA} + \text{TR}}{\text{TA} + \text{TR} + \text{FA} + \text{FR}} \quad (1)$$

where TA + TR + FA + FR are the numbers of each type of decision: true acceptance (TA), true rejection (TR), false acceptance (FR), and false rejection (FA).

Results and discussion

In the field of biometric gender recognition and classification, there are a large number of studies using different methods for feature extraction and classification. However, after reviewing the databases, Web of Science (WoS) and Scopus, it is clear that there is a lack of research specifically dealing with the topic of drone or UAV, gender recognition, and thermal image, the only exception being a conference paper by the authors (Příhodová and Jech 2021). WoS and Scopus were searched in July 2023. In the mentioned databases, however, some studies deal with some parts of the topic.

Chen and Ross (2011) recognised gender from thermal facial images, but these were not acquired using a drone. Thanks to this, the faces in the pictures could be captured in

Fig. 10. Examples of pre-processing thermal images obtained by drone.

Table 2. Comparison with related works.

Sources	Techniques applied for recognition	Size of the database	Data resolution/environment	Accuracy
Chen and Ross (2011)	LBP/SVM LBP/random forest	Private, 1003 thermal images	480 × 640 pixels interior	90.41% 85.55%
Prihodova and Jech (2021)	CNN—AlexNet	FATFD 2500 + Private drone Phantom with thermal camera 203 thermal image	160 × 120 pixels exterior	82.3%
Rafique (2019)	CNN	Faces dataset 17 603 visible images	– exterior/interior	84.7%
Shan (2012)	LBP/SVM	More databases, 17 814 visible images	– exterior/interior	92.89%
Wang et al. (2016)	Thermal statistical temperature and LBP/Bayesian networks	NVIE 532 and Equinox 1269 visible and thermal image	320 × 240 interior	83.3% 86.2%
Zhang et al. (2018)	MS3F	Images of Groups (IoG) 5050 visible images	Various interior/exterier	86.1%
Proposed procedure	CNN—AlexNet	FATFD database 2500 + OCD dataset 252 thermal images	160 × 120 pixels exterior	82.9%
Proposed procedure	CNN—VGG-16	FATFD database 2500 + OCD dataset 252 thermal images	160 × 120 pixels exterior	82.4%
Proposed procedure	CNN—VGG-19	FATFD database 2500 + OCD dataset 252 thermal images	160 × 120 pixels exterior	85.5%

the interior and in the frontal position. The images are also at a higher resolution of 480 × 640 pixels than our database has. Both facts facilitate classification. For feature extraction and classification, they used classic methods in the proposed process CNNs are used. Rafique (2019) used visible facial images for gender recognition, some of which were not of good quality, and used his CNN for classification extraction. However, facial images were not obtained using a drone and would therefore be challenging to use in public spaces. Shan (2012) and Zang et al. (2018) use visible face images were not acquired in low-light conditions but also not acquired using a drone, which is a disadvantage under certain conditions.

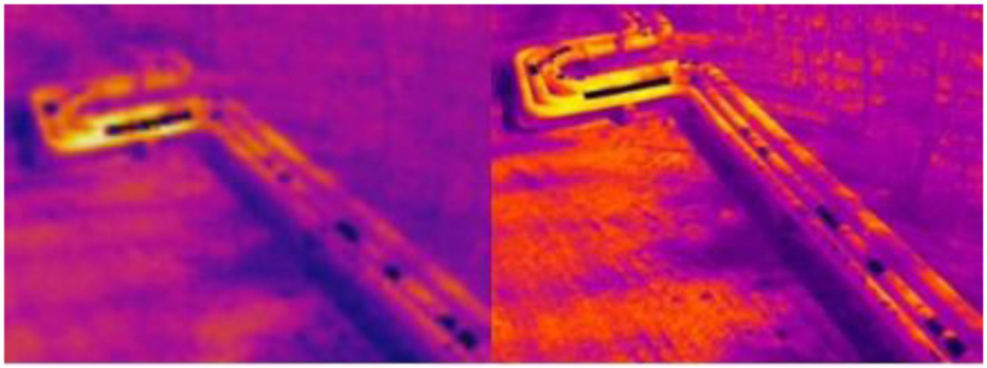
Therefore, this paper fills the gap by exploring the potential of drone-acquired facial thermal images for gender recognition purposes. The achieved classification accuracies, especially for the VGG-19 (85.5%) model, are good and testify to the potential of the proposed procedure. The results of the proposed procedure compared to other works are in Table 2.

In previous studies, thermal images were not taken outdoors, the diversity of the outdoor environment may be a factor leading to reduced classification accuracy compared to using thermal images taken indoors. Another disadvantage for classification is the low resolution of the images. These aspects of input data quality have a direct impact on the results of our research and their comparison with existing implementations.

In none of the related works, data are collected using drones, even though drones for data collection have many advantages (Heatherly, 2014; Ruwaimana et al., 2018) and based on our own experience):

- Accessibility: Drones can easily reach and monitor areas that might be difficult to access for humans.
- Cost-effective: In many scenarios, utilising drones can be more cost-effective than manual data collection methods or using manned aircraft, especially for large-scale or repeated tasks.
- Real-time data collection: Drones equipped with the necessary sensors and cameras can provide real-time data, which can be invaluable for time-sensitive applications.

Fig. 11. DJI Mavic 2 DUALversus DJI Mavic 3T.



- However, the use of drones for data collection also has its disadvantages.
- Privacy concerns: Using drones can raise significant privacy concerns, especially when monitoring populated areas. Unintended capture of private moments can lead to ethical and legal issues.
- Limited battery life: Drones typically have a limited flight duration due to battery constraints, which might limit the extent or duration of data collection sessions.
- Weather dependency: Drones can be affected by adverse weather conditions such as strong winds, rain, or fog, which might compromise the quality of data or even the safety of the drone.
- Regulatory restrictions: Many countries have established regulations around drone usage, especially in urban areas or near critical infrastructures, which can limit their deployment.

In addition to the general disadvantages of the drone for data collection, in our solution can be seen as a disadvantage in the used drone. In the future, it is possible to focus on improving the quality of the input data obtained using more suitable drones for taking thermal images. A suitable choice is the DJI Mavic 2 Enterprise ADVANCED or DJI Mavic 3T, which has a built-in HD thermal camera with a resolution of 640 × 512 pixels at 30 Hz, which is a 17× increase on the effective pixels; see Fig. 11 to compare output thermal images. Thermal images are taken by a radiometric sensor in R-JPEG image format. This drone allows obtaining images from higher flight levels while maintaining image quality.

Conclusion

The evolving realm of biometric recognition continuously seeks innovative approaches to enhance accuracy and practical application. This study has successfully highlighted the underexplored potential of combining drone technology with thermal images for gender recognition.

The proposed procedure, with its unique convergence of technologies, offers several notable advantages. This procedure can be applied on-demand with some limitations, like flight legislation. The next benefit is the speed of the proposed procedure, which can be processed in a short time when powerful hardware is used. There is no need of complex infrastructure of all kinds of materials.

By achieving high classification accuracies with models like VGG-19, this research has validated the efficacy of this method and paved the way for further explorations in this domain. Future research can focus on combining thermal images with other types of images, such as RGB images. Research in multimodal analysis could lead to more efficient models with higher accuracy. In addition to gender recognition, it could be interesting to detect other characteristics from thermal images, such as age, emotional state, or health status of persons. This would expand the range of applications of drones in the field of human behaviour analysis.

As biometric recognition shifts with emerging technologies, the findings of this study underscore the importance of interdisciplinary approaches and the need for rigorous ethical considerations. However, this is beyond the scope of this study.

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Data availability

Data generated or analysed during this study are not available due to the nature of this research. We do not have consent to disclose images from all the subjects photographed.

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Investigation: JJ
Methodology: KP, JJ
Project administration: JJ
Resources: JJ
Software: JJ
Validation: KP, JJ
Visualization: KP, JJ
Writing – original draft: KP, JJ

Competing interests

The authors declare there are no competing interests.

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