ENHANCED CONTEXTUAL BASED DEEP LEARNING MODEL FOR NIQAB FACE DETECTION

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ABSTRACT

Human face detection is one of the most investigated areas in computer vision which plays a fundamental role as the first step for all face processing and facial analysis systems, such as face recognition, security monitoring, and facial emotion recognition. Despite the great impact of Deep Learning Convolutional neural network (DL-CNN) approaches on solving many unconstrained face detection problems in recent years, the low performance of current face detection models when detecting highly occluded faces remains a challenging problem and worth of investigation. This challenge tends to be higher when the occlusion covers most of the face which dramatically reduce the number of learned representative features that are used by Feature Extraction Network (FEN) to discriminate face parts from the background. The lack of occluded face dataset with sufficient images for heavily occluded faces is another challenge that degrades the performance. Therefore, this research addressed the issue of low performance and developed an enhanced occluded face detection model for detecting and localizing heavily occluded faces. First, a highly occluded faces dataset was developed to provide sufficient training examples incorporated with contextual-based annotation technique, to maximize the amount of facial salient features. Second, using the training half of the dataset, a deep learning-CNN Occluded Face Detection model (OFD) with an enhanced feature extraction and detection network was proposed and trained. Common deep learning techniques, namely transfer learning and data augmentation techniques were used to speed up the training process. The false-positive reduction based on max-in-out strategy was adopted to reduce the high false-positive rate. The proposed model was evaluated and benchmarked with five current face detection models on the dataset. The obtained results show that OFD achieved improved performance in terms of accuracy (average 37%), and average precision (16.6%) compared to current face detection models. The findings revealed that the proposed model outperformed current face detection models in improving the detection of highly occluded faces. Based on the findings, an improved contextual based labeling technique has been successfully developed to address the insufficient functionalities of current labeling technique.

ABSTRAK

Pengecaman wajah manusia merupakan salah satu bidang yang paling banyak dikaji dalam visi komputer yang memainkan peranan asas sebagai langkah pertama dalam semua sistem pemprosesan wajah dan analisis wajah seperti pengecaman wajah, pemantauan keselamatan dan pengecaman emosi wajah. Walaupun terdapat impak yang besar daripada pendekatan Rangkaian Neural Konvolusi-Pembelajaran Mendalam (DL-CNN) dalam menyelesaikan masalah pengecaman wajah tanpa batasan dalam tahun-tahun kebelakangan ini, prestasi yang rendah pada model semasa pengecaman wajah apabila pengecaman wajah yang terhalang masih lagi kekal menjadi masalah yang mencabar dan wajar dikaji. Cabaran ini semakin ketara apabila halangan pada wajah itu menutupi sebahagian besar wajah yang seterusnya secara dramatik mengurangkan bilangan ciri-ciri perwakilan dipelajari yang digunakan oleh Rangkaian Penyarian Sifat (FEN) untuk membezakan bahagian-bahagian wajah daripada latar belakang. Kekurangan set data wajah yang terhalang dengan imej yang mencukupi bagi wajah yang terhalang dengan teruk merupakan cabaran lain yang mengurangkan prestasi pengecaman. Oleh itu, kajian ini menangani masalah prestasi rendah dan membangunkan model pengecaman wajah terhalang yang dipertingkat untuk mengecam dan mengesan dengan tepat wajah-wajah yang terhalang dengan teruk. Pertama, set data wajah-wajah yang terhalang dengan teruk dibangunkan untuk menyediakan contoh latihan mencukupi digabungkan dengan teknik penganotasian berdasarkan kontekstual untuk memaksimumkan jumlah ciri-ciri wajah yang menonjol. Kedua, dengan menggunakan latihan separuh daripada set data, sebuah model Pengesanan Wajah Terhalang (OFD) Pembelajaran Mendalam-CNN dengan ciri pengekstrakan dan rangkaian pengecaman dipertingkat telah dicadangkan dan dilatih. Teknik pembelajaran mendalam yang lazim, iaitu teknik pembelajaran pemindahan data dan teknik peningkatan data diguna pakai untuk mempercepatkan proses latihan. Pengurangan positif-palsu berdasarkan strategi maksimum-masuk-keluar diguna pakai untuk mengurangkan kadar positif-palsu yang tinggi. Model yang dicadangkan dinilai dan ditanda araskan dengan lima model pengecaman wajah semasa di set data. Hasil yang diperoleh menunjukkan bahawa OFD mencapai prestasi yang lebih baik dari segi ketepatan (purata 37%) dan purata ketepatan (16.6%) berbanding dengan model pengecaman wajah semasa. Hasil kajian mendedahkan bahawa model yang dicadangkan mengatasi model pengesanan wajah semasa dengan ketara dalam menambah baik pengecaman wajah-wajah yang terhalang teruk. Berdasarkan dapatan, satu teknik pelabelan berdasarkan kontekstual yang dipertingkat berjaya dibangunkan untuk mengatasi ketidakcukupan fungsi-fungsi teknik pelabelan semasa.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

Adaboost	-	Adaptive boosting
ACM	-	Association for Computing Machinery
ATM	-	Automated Teller Machine
CNN	-	Convolutional Neural Network
CPU	-	Central Processing Unit
DL-CNN	-	Deep learning Convolutional Neural Network
DN	-	Detection Network
DPM	-	Deformable Part Model
Fast-RCNN	-	Fast Region-based Convolutional Neural Network
Faster-RCNN	-	Faster Region-based Convolutional Neural Network
FDDB	-	Face detection database
FEN	-	Feature Extraction Network
FN	-	False Negative
GIoU	-	Generalized Intersection Over Union
GPU	-	Graphical Processing Unit
FP	-	False Positive
GT	-	Ground truth
HCI	-	Human-Computer Interaction
HOG	-	Histogram of Gradient
IOU	-	Intersection over Union
LBP	-	Local Binary Patterns
MAFA	-	Masked Faces
ML	-	Machine Learning
MTCNN	-	Multi-Task Cascaded Convolutional Neural Networks
NMS	-	Non-Maximum Suppression
OFD	-	Occluded Face Detection
PC	-	Personal Computer
PCA	-	Principal Component Analysis
RAM	-	Random Access Memory

R-CNN	-	Region-based Convolutional Neural Network
RGB	-	Red Green and Blue
RPN	-	Region Proposal Network
SSD	-	Single Shot Detection
YCbCr	-	Luminance; Chroma: Blue; Chroma: Red
YOLO	-	You Only Look Once

LIST OF APPENDECES

OPERATIONAL DEFINISIONS

Extended five face-regions: is a classification of the face regions into five equal areas, i.e., forehead ,two eyes, nose, mouth and chin, the purpose of this classification is to measure the degree of face occlusal based on the number of occluded regions.

Face regions: are all face related areas that include the forehead, the two eyes and elbows , nose , mouth and chin.

Facial features: facial features can be defined as the distinguishing characteristics of the face that can be described in terms of the size and shape of the entire face and its component parts, which include the two eyes, two ears, nose, mouth, and chin.

Feature extraction network is a convolutional neural network (CNN) composed of set of network layers which process an input image and extract the distinctive features, the extracted features are then forwarded to another CNN network called detection network for classification and detection of targeted objects.

Heavily occluded face: is a face in a digital image with high degree of occlusion, in which four face regions of the face (or more) are blocked by any type of occlusion as in face with niqab for instance.

Image annotation and labelling: is the process of adding metadata in a form of bounding box coordinates of the faces in the images of the dataset to be used as ground truth for the training of deep learning convolutional neural network models.

Niqab: A niqab is a face covering veil which is worn by minority of Muslim women for a religious purpose to cover their faces while being outdoor or among none relatives. Niqab hides most of the face landmarks and sometimes leaves only the two eyes and some parts of the nose.

Niqab-face: is a woman face with niqab covering veil, normally all the face is covered except of the two eyes. Niqab face is considered highly occluded face (since four or more faces regions are hidden).

Occluded face: a face is considered occluded in the digital image if at least one face area is hidden or blocked by any object such as face mask, sun glasses, niqab. Or any other object which hides facial features to be detected.

CHAPTER 1

INTRODUCTION

1.1 Introduction

Finding faces using the visual system is a trivial task that humans can do effortlessly in their daily life, but building machines or robots with vision ability is probably one of the most challenging problems, which humans try to solve. During the past three decades, the computer vision community started to pay attention to face processing as well as other researchers such as psychophysicists and neuroscientists, which have widely investigated recently, many commercial applications and research demonstrations are obtained and developed from these efforts (Voulodimos et al., 2018). The human face is among the most important and informative object that tells a person’s race, sex, identity, age emotion, and more in just a glimpse of a second, the demand of finding a face in digital images or videos has been incrementally increased recently due to wide practical applications in multimedia, biometric systems, surveillance, security applications and human-computer interaction (HCI) (Guo and Zhang, 2019; Tsao and Livingstone, 2008).

Face detection is a sub-task of object detection under the domain of computer vision (Zhao et al., 2019). It has been under hot investigation for more than two decades and still an active area of research in computer vision (Masi et al., 2018; Zhang and Zhang, 2010). It is the first step of all face-application-related including face recognition, face verification, face tracking, and facial expression detection (Zhao et al., 2019; Kortli et al., 2020). It is the building block for more sophisticated systems developed for consumer products like digital cameras, social networks, smartphone apps, etc. (Zafeiriou et al., 2015; Tikoo and Malik, 2017). Figure 1.1 represents the research area according to the Association for Computing Machinery Digital Library (ACM) classification system (Acm, 2012).

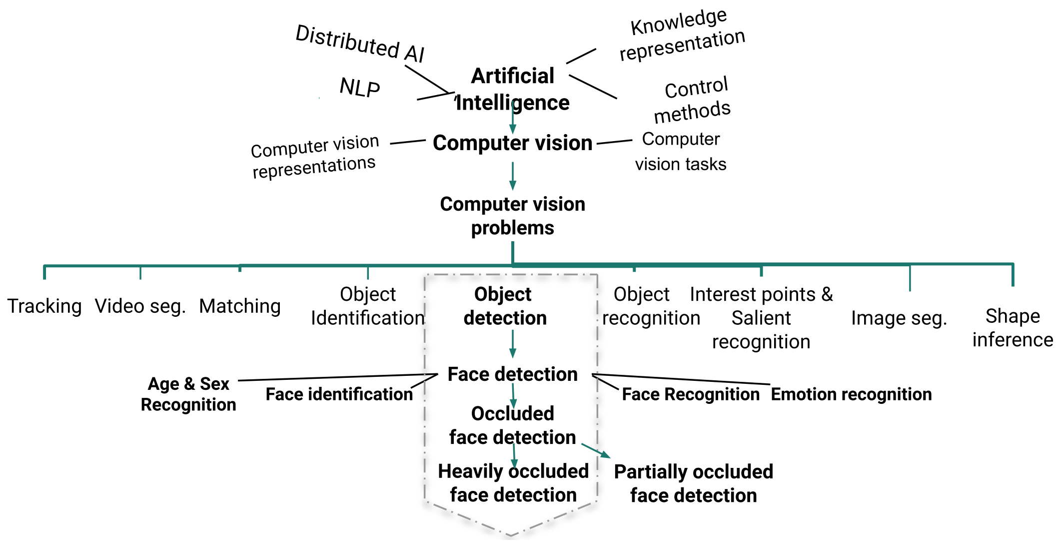


Figure 1.1 Research Focus Area

The enormous applications of face detection motivate researchers to find ways of improving its accuracy and performance. Hundreds of research papers had proposed several approaches for detection methods, the advancement before 2001 had been nicely surveyed and grouped by Hjelmås and Low (2001); (Zhang and Zhang, 2010). However early works within that period were inapplicable in real-world situations until the distinguished work of Viola and Jones (2001) which made face detection feasible and enabled the implementation of face detection in real-world applications, such as in digital cameras and photo software organization, due to the brilliant ideas which used a successful combination of machine learning with feature invariant techniques (Zafeiriou et al., 2015; Zhang and Zhang, 2010).

Since then, great progress has been made to boost the performance, for instance, deformable part models (DPM) were proposed to model face parts (Felzenszwalb et al., 2010). Histogram of Gradient (HOG) introduced by Dalal and Triggs (2005), Local Binary Patterns (LBP) by (Chehrehgosha and Emadi, 2016), and Integral Channels by Wang et al. (2009a) had a significant impact on face detection to achieve better accuracy on frontal faces in controlled environments, where no extreme variations of illumination and lighting conditions. All these aforementioned approaches were mainly dependent on manually designed and handcrafted features and classifiers (Li et al., 2019b).

The emergence of deep learning and convolutional neural network (DL-CNN) have recently shown remarkable successes and dominated various computer vision tasks such as image recognition, object detection, and face detection (Hao et al., 2017; Liu et al., 2020). Unlike hand-crafted features in machine learning as in Haar-features for instance DL-CNN is a hierarchical deep-learning approach that has been successfully applied as a powerful features extraction, that extracts and learns high-level representation features from a vast amount of training data (Alafif et al., 2017). Impressive progress has been made in detecting human faces from digital images where an average performance of 98% is achieved by Hu and Ramanan (2017) in the unconstrained face-detection benchmark.

Among the challenges in the design of face detection is the low performance of face detectors when detecting faces in certain scenarios due to illumination differences, facial expression changes, pose variations, and with the presence of occlusion which appears when covering faces either in partial or in total (Chen et al., 2018b). In fact, an accurate face detection model as a primary stage of any human face processing system has a major influence on the overall performance and usability of the entire practical applications.

1.2 Problem Background

The goal of face detection is to determine the existence of a face in an image, therefore, if a face exists, return its location in a form of bounding box coordinates for each face (Ranjan et al., 2018). It should be able to find faces among all non-face objects (Zhang and Zhang, 2010). Various face-related applications require face detection as a pre-processing step for finding face location, many of the techniques are proposed for these applications assume that the location of the face is pre-identified and available for the next step, therefore all these systems for sure will fail if face detection fails to accurately allocate the face (Zhao et al., 2019).

Detecting faces in constrained conditions where images are taken in controlled settings, with a fixed distance from the camera, and with specific pose and lighting conditions as in the frontal face, for instance, is no longer a challenging task (Masi et al., 2018) and is considered a solved problem (Guo and Zhang, 2019). It was made possible since 2001 after the aforementioned work of Viola and Jones (2001). They used haar-like features with adaptive boosting (Adaboost) designed in a cascaded manner and integral image. Modern face detection systems can straightforwardly detect faces in near-frontal and are embedded in e-albums and digital cameras (Yang et al., 2016a).

However, face detection models have to be able to detect not just the frontal faces, but they also have to deal with faces of various scales, poses, and appearances and with the presence of occlusion that can change the overall appearance of the face (Li et al., 2018; Yang et al., 2002).

The high variations of face orientation, facial expression, and occlusion in an unconstrained environment where images are taken in different illumination variations and occlusion is a challenging problem for face detection systems and may degrade the performance of the detection, it may also be responsible for the increase of the false detection rate (Chen et al., 2018b; Zafeiriou et al., 2015). The following factors are considered the main challenges associated with face detection performance:

(a) **Pose**: The position of the face in images may differ due to variation in-plane rotation (frontal, half profile, profile, upside down), and some facial features such as eye or nose may become partially or fully occluded (Moallem et al., 2015).

(b) **The existence of certain facial components:** some facial components like glasses, caps, mustaches, and beards, for instance, can exist or not on the face, these components vary greatly in their form, color, and size (Sharifara et al., 2014).

(c) **Facial expression:** the appearance of faces such as happiness, angriness, or sadness can directly affect a person’s facial expression (Dagar et al., 2016).

(d) **Image orientation and Illumination:** when the camera's optical axis varies, image orientation will exist and be formed, other aspects like illumination and lightning variant intensity, and camera calibration (sensor-response, type, and size of lenses) (Zou et al., 2007).

(e) **Scale variations and small face: s**mall faces in crowed in which an image could have tens or hundreds of faces makes the detection task difficult and lower the performance of face detection models (Bai et al., 2018).

(f) **Occlusion:** when some or more parts of the face is unavailable, either blocked by other object or covered by face-veil partially or in total (Peng et al., 2020; Chen et al., 2018b).

The existence of one or more of the aforementioned challenges may degrade the performance of face detectors. A lot of progress has been done to improve the performance of face detectors under many unconstrained scenarios. Many previous researches have addressed these challenges of unconstrained scenarios (Chen et al., 2014; Li et al., 2015; Mathias et al., 2014). For example, pose, scale, and lighting variations were addressed by feature invariant approaches which focused on finding face features robust to changes in pose and lighting (Zafeiriou et al., 2015).

The recent improvement of face detection in the unconstrained scenario could be attributed to two factors, i) the emergence of deep learning approaches that have a direct impact on the extraction of facial representative features and analysis tasks, which enabled the existence of sophisticated face detections models, and ii) the availability of large-scale face detection datasets with varieties of training images (Nada et al., 2018).

Deep learning has been recently behind the great advancement of object detection and face detection (Liu et al., 2020; Zhao et al., 2019; Liang et al., 2020). The application of DL and CNN layers have provided excellent feature extraction and learning methods for accurate face detection models, while multi-stage region proposal network and single-stage detection such as Faster-RCNN proposed by Ren et al. (2015) and YOLO introduced by Redmon and Farhadi (2017) have significantly enhanced the performance of face detection in an unconstrained environment. The availability of public face detection datasets such as Annotated Faces in The Wild (AFW) (Zhu and Ramanan, 2012), FDDB (Jain and Learned-Miller, 2010), and Widerface (Yang et al., 2016a) have contributed to the advancement in face detection research.

Despite the progress that has been achieved in face detection, detecting faces in certain scenarios as in face with occlusion has not reached saturation yet, there have been open questions that remains unsolved and has to be explored more when dealing with occlusion (Yang et al., 2018; Mathias et al., 2014). Face detection under patrial or heavy occlusion remains a challenge to face detection algorithms and worth investigation (Chen et al., 2018b; Alafif et al., 2017).

Although the detection of heavily occluded faces is critical for several applications, it is highly demanded for security monitoring and people-counting applications. Very few researches have been done in that direction and directly addressed the detection under occlusion. For example, Hotta (2007) used local features with Support Vector Machine (SVM) to detect faces under partial occlusion, Chen et al. (2017) proposed an occlusion aware framework based on convolutional neural network model to address the occlusion problem in face detection, Alafif et al. (2017) trained a single CNN model on large partial occluded faces images to detect unconstrained multi-view partially occluded and non-partially occluded faces.

Faces under partial occlusion have been addressed in general as in the aforementioned works, however, the challenge of highly occluded faces was not considered. In heavily occluded faces most of the face features are hidden and blocked due to the occlusion.

Occluded face or face under occlusion usually appears when the face is covered or blocked either in partial or in total, which is due to work requirement such as medical masks as in hospitals or due to pandemic awareness of the current COVID-19, it could be also due to religious concern as in some Muslim societies where Muslim ladies wear niqab, a face covering veil, which is a practice of veiling their faces while being outdoor or in the presence of non-relatives (Khan, 2016; Zempi, 2016).

The word ‘Niqab’ is used to refer to head and face covering worn by Muslim women, thus they can often be distinguished by the way they dress and cover their faces (Chowdhury et al., 2017a). Figure 1.2 shows examples of heavily occluded faces for some Muslim women are wearing the niqab veil in different cultural styles referred as niqab, burqa or khimar (Chowdhury et al., 2017b; Khan, 2016). The whole faces are hidden and almost covered and blocked by niqab; therefore, faces are heavily occluded.

Figure 1.2 Examples of heavily occluded faces with different niqab styles

There are some researchers who tried to define occluded faces according to the degree of occlusion. For example, in Yang et al. (2016a) they classified face under occlusion into three categories: face with no occlusion, partially occluded faces, and heavily occluded faces. Partially occlusion is defined as a face where 1% to 30% of its area is occluded, whereas heavily occlusion is when more than 30% of the face area is covered or blocked.

In Ge et al. (2017) they divided the face into four main regions as shown in Figure 1.2 section (a), these major regions are chin, mouth, nose and the eyes. they defined the degree of occlusion based on the number of occluded regions; therefore, weak occlusion is where one to two regions are occluded, medium occlusion is with three regions and heavy occlusion is when there are four occluded regions.

However, it seems a loose classification when defining heavily occluded faces as faces occluded or covered with over 30%. There is a concern with describing highly occluded faces, defining heavily occluded faces when four regions are occluded still not cover all the heavily and fully occluded faces. Therefore, based in Ge et al. (2017) instead of four regions we extend the classification of the face regions into five equal areas which include the forehead, the two eyes, the nose, the mouth and the chin, so that heavily occluded and fully occluded can be distinguished by the number of occluded areas.

The degree of heavily occlusion is shown in Figure 1.3 and 1.4. below. Figure 1.3 section (a) shows the four face regions of Ge et al. (2017). The extended five-regions are shown in section (b). Section (c) shows the overlay of the extended five-regions with the four regions of Ge et al. (2017) in order to emphasis and point out the distinction between the two definitions. Section (c) shows an example of a face heavily occluded with four occluded regions according to Ge et al. (2017), however the degree of occlusion is approximately 50% when overlaid by the extended five-regions. Figure 1.4 shows faces in high degree of occlusion with four occluded regions. The faces are arranged according to the number of occluded areas, from left to right. Although all faces are considered heavily occluded according to the four occluded area definition of Ge et al. (2017), however there is still a distinction in the degree of occlusion between the faces from left to right which ranges from 70% till 100% of full occlusion, the degree of occlusion can be measured more clearly when using the extended five face regions.

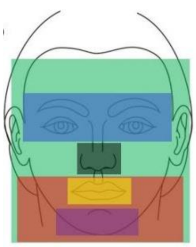
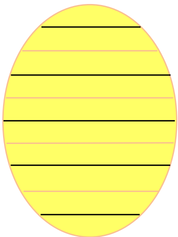
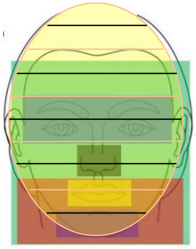
				
(a) The four face regions (Ge et al., 2017)	(b) The Face oval divided into five regions	(c) The five-face-regions is overlied on foue-face regions	(d) Heabvily occluded face with four occluded regions according to Ge et al. (2017)	(e) 50% of occluded areas

Figure 1.3 The four-regions of the occluded face of Ge et al.(2017) alongside with the five-regions

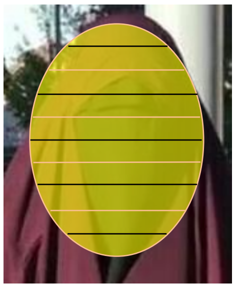
Variations of heavily occluded faces				
Five occluded regions overlaid on heavily occluded faces				
	occluded area $\geq$ 70%	occluded area $\geq$ 80%	occluded area $\geq$ 90%	occluded areas $\approx$ 100%

Figure 1.4 High occluded faces covered with niqab in different degree of occlusion

The existence of recently proposed large-scale datasets has attributed to the high performance of face detection models which almost recent state-of-the-art deep learning-CNN face detection models have leveraged a large amount of training dataset and the powerful features extractors network of deep-CNN (Nada et al., 2018). The amount of training images used during the training determines the performance of the detector (Shepley, 2019; Kim et al., 2018).

Among the reasons that may explain why the performance of recent face detectors decrease and perform poorly when the occlusion is very high as in face covered with niqab for instance in which the occlusion blocks most of the face area is the lack of a large-scale dataset with abundant training images of particular scenarios as in images with faces covered with niqab. Several face detection datasets have been recently released. For example, Widerface proposed by Yang et al. (2016a) and FDDB proposed by Jain and Learned-Miller (2010) and were used for training and testing of current face detection models (Chen et al., 2017). For instance, MTCNN and TinyFace models which were proposed by Zhang et al. (2016) and Hu and Ramanan (2017) respectively were both trained on Widerface dataset.

Though these datasets may contain thousands of images with different pose rotation, different lighting, and some degree of occlusion. However, the high degree of occlusion scenario particularly, as in faces covered with a niqab has not existed among them. This led to the inability of current face detectors to successfully detect heavily covered faces as in niqab-face for instance, which is regarded as a consequent result of the absence of sufficient representative features extracted and learned by CNN-based face detection models during the training. Many state-of-the-art face detection models were initially trained on Widerface dataset which contains 18,839 images with faces in different poses and occlusion but with a limited amount of images of highly occluded faces, except for a few images with faces covered with medical masks and not sufficient for the training (Hu and Ramanan, 2017; Zhang et al., 2016) (Li et al., 2020; Llinzai, 2019).

Another assumption that may influence the performance of recent face detection models and contribute to their poor performance when detecting faces in a high degree of occlusion, is associated with the occlusion problem itself (Li et al., 2019a). Excessively, occluded faces have diminished discrimination and very few features due to occlusion, unlike typical faces with salient features (Shepley, 2019). Therefore, the existence of occlusion limits the distinctive features of faces and restricts the number of learned representative features during the training (Chen et al., 2018b).

1.3 Problem Statement

Face detection as the first and the fundamental step of any automated face processing and facial analysis systems motivates researchers to find ways of improving the accuracy and performance of the system. An accurate face detection system has a direct impact on the overall performance and accuracy of all face-related applications such as face recognition, face identification, security monitoring, and facial emotion detection. A robust face detection model should be effective under arbitrary variations in pose and occlusion; however, it is still an unresolved problem, one of the challenges in the design of face detection is the low performance of face detectors when detecting occluded faces.

A substantial gap exists between the accuracy of existing face detectors and the expected performance in the case of a high degree of occlusion. Several approaches were proposed to address the problem of partially occluded faces; however, the challenge of highly occluded faces was not considered, the problem of a high degree of occlusion where the majority of the face is covered still remains a challenge. State-of-the-art face detectors still have problems in dealing with faces in a high degree of occlusion. This challenge has not yet been entirely solved. The degree of occlusion has a direct effect on the performance of face detection, the detection rate decreases as occlusion level increases.

The lack of available labeled dataset of highly occluded faces with large and sufficient numbers of images with faces in varieties of a high degree of occlusion to be used for training of occluded face detectors broadens the existing gap. The scarcity of salient representative features in highly occluded faces complicates the task of the feature extraction network and restricts its ability to learn adequate discriminative features from the training examples during the training.

The general research question is how to enable face detection models to be able to detect and localize heavily occluded faces on digital images? Therefore, this thesis aims to design and develop an improved deep learning occluded face detection model for detecting heavily occluded faces as in faces covered with niqab for example.

1.4 Research Goal

The goal of this research is to propose and design an enhanced heavily occluded face detection model which is capable of detecting faces in a high degree of occlusion as in faces covered with niqab. The degree of occlusion in faces with niqab ranges from 50% to 90% (as illustrated previously in Figure 1.4) where most of the face features are hidden.

1.5 Research Objectives

To achieve the research goal, the following objectives must be accomplished:

1) To propose an occluded face detection dataset that takes into account the properties of heavily covered faces suitable to be used for deep-learning face detection training and evaluation.

2) To design a contextual-based deep learning scheme for enhancing the representative features with an improved feature extraction network of the heavily covered faces to improve the detection performance.

3) To propose a deep-learning-CNN face detection model capable of detecting faces in a high degree of occlusion where most of the face is veiled in unconstrained environment.

1.6 Research Scope and Limitation

The proposed occluded face detection (OFD) model is introduced to address occluded faces. Although, it potentially can deal with un-occluded faces such as frontal and unconstrained faces, however, the focus is more on heavily covered faces as in faces in niqab for instance.

This research is concerned with occluded face detection, mainly focused on heavily occluded faces which results due to wearing of the face-covering veil, with the aim to improving face detection performance under a high degree of occlusion as in heavily covered faces with niqab which is referred to as niqab-face. The focus on heavily covered faces is different from other types of occlusions which result due to the crowds for instance, so that, some faces are occluded by other faces or objects and may suffer from low-resolution quality due to crowd which makes it difficult to be detected.

Heavily covered faces may have no resolution issue, an image may contain one face only as shown previously in Figure 1.2 for instance, however, it may not be detected successfully, due to the poor performance of current face detection models, because they were not exposed to sufficient training examples of images that contain faces with similar type of occlusion, and also due to the limited features on occluded faces.

Since the unconstrained environment has extreme variations in where faces could appear, this research is constrained on occluded faces with a resolution not less than 80x80. Occluded faces in low resolution images are very hard to be detected this is because face in occlusion is already have limited features, therefore low-quality images and low resolutions make it very difficult to find the representative face features and harden the task of feature extraction to find distinguished features on low resolution images. On the other hand, images with occluded faces in extreme pose and poor illuminations are also another burden that makes the detection worse.

The following scenarios are considered out of the research scope.

- Small faces with high occlusion as in crowded faces or with extreme lighting and in low-quality images.
- Faces in extreme pose with high degree of occlusion are not addressed in this research.

1.7 Significance of the Study

It is expected that the proposed occluded face detection model will improve the performance of the detection of highly occluded faces since all face-related applications rely on face detection as an essential preprocessing step, therefore their overall performance and accuracy will be improved accordingly.

It is also expected that the proposed occluded face dataset as training and benchmark publicly available dataset will contribute to the improvement of current face detection researches and models. The idea of utilization of contextual information of occluded faces and the improvement of the feature extraction network is expected to attract other researchers to be used for similar situations.

1.8 Thesis Organization

This thesis is organized as follows.

Chapter 2 provides a comprehensive literature review of the related area highlighting problem background and existing solutions in the context of deep learning and occluded face detection. It started with the importance of face detection for all face-related applications, followed by a briefing of face detection challenges. More focus was shed on the remaining challenges related to occlusion. Two popular approaches for addressing face detection challenges were briefly discussed, more concern was given to the deep learning convolutional neural network approach as it gained a positive record in solving most of the computer vision and object detection tasks. Recently available solutions have made use of contextual information for addressing occlusion and small face issues in face detection with more attention on occluded face detection. The available solutions are discussed to highlight the novelty of this research. A review of face detection datasets was provided along with a comprehensive discussion. Research direction was highlighted with illustration on current challenges on dataset and availability of feature representation. Finally, a summary was provided.

Chapter 3 describes the research methodology to guide as a roadmap to achieve and verify research objectives, all required phases for designing and developing the proposed model were briefly highlighted.

Chapter 4 presents the design and implementation of the proposed occluded face detection model. All phases related to the design are described and illustrated in detail. The first phase of dataset construction, then Occluded face detection model design, the last phase related to the implementation involves training and evaluation of the proposed model.

Chapter 5 provides details of the experimental configurations and evaluation results of the proposed OFD model and the current benchmarked face detection models. Details analysis of the obtained result was interpreted, discussed, and compared with current models.

Chapter 6 provides a conclusion about this study by emphasizing contributions and recommended future direction and possible further enhancement of this research.

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LIST OF PUBLICATIONS

Indexed Journal

1. **Alashbi, A. A. S**., Sunar, M. S., and Alqahtani, Z. (2022). Deep-Learning-CNN for Detecting Covered Faces with Niqab. *In International Journal of Information Technology Management JITM)* ,Special Issue, 114-123 **(Indexed by SCOPUS)**.

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1. **Alashbi, A. A. S.,** Sunar, M. S., and Alqahtani, Z. (2020, December). Context-Aware Face Detection for Occluded Faces. *In 2020 6th International Conference on Interactive Digital Media (ICIDM)* (pp. 1-4). IEEE. https://doi.org/DOI: 10.1109/ICIDM51048.2020.9339647. **(Indexed by SCOPUS)**

2. **Alashbi, A. A. S**., and Sunar, M. S. (2019). Occluded Face Detection, Face in Niqab Dataset. *In International Conference of Reliable Information and Communication Technology*, (pp.209-215). Springer, Cham. https://doi.org/DOI/10.1007/978-3-030-33582-3_20. **(Indexed by SCOPUS)**

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1. **Alashbi, A. A. S.**, and Sunar, M. S. (2019). Face detection for covered faces, detecting a face in niqab. On universal wellbeing (issue 2019), 92.