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Scene Perception using Machine Pareidolia of Facial Expressions

by

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Abstract

The aim of this thesis is to pursue the question, ‘Can a machine describe the emotional response to a scene using perceived faces and facial expressions?’. To establish the relevance of this interdisciplinary thesis question literature research was conducted not only in Computer Science but also in the disciplines of Cognitive Science and Psychology. The findings from this research revealed that humans can produce an emotional response to a scene using the facial expressions of perceived faces and face-like patterns, and this is achieved at a conscious and subconscious level, as well as beyond our visual focus. These findings provide the foundations for addressing the thesis question in the realm of computer vision and machine learning. A new face model, a new face detection algorithm and a new machine learning technique based on Support Vector Machines (SVMs) was developed and an extensive experimental evaluation was conducted. The new machine learning technique called ‘Pairwise Adaptive SVM’ (aka, *pa*-SVM) uses a refined parameter selection process for training, and was tested using real world datasets. The result is an improved detection and classification of faces and face-like patterns, as well as their associated facial expressions. The outcome is a machine that is capable of describing the emotional response to a scene using pareidolia of faces and facial expressions.

Declaration

This thesis contains no material which has been accepted for the awards of any other degree or diploma in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. I give consent to this copy of my thesis, when deposited in the University Library[1], being made available for loan and photocopying subject to the provisions of the Copyright Act 1968.

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List of Acronyms

kNN k Nearest Neighbour

ANN Artificial Neural Network

ECOC Error Correcting Output Code

ELM Extreme Learning Machine

ICA Independent Component Analysis

LBP Local Binary Patterns

LDA Linear Discriminant Analysis

PCA Principal Component Analysis

PDFC Positive Definite Fuzzy Classifier

SVM Support Vector Machine

CHAPTER 1

Introduction

Contents

You are currently standing in the middle of a suburban area and observing a row of houses. A feeling in your gut says one house seems not to belong, or perhaps one house stands out to your liking. When asked whether you can see a face in this particular house, to some this may not be obvious at first, however to many they can almost instantly perceive areas of the house where an eye would be, and then a mouth. By taking a step back, you see another face and this time the neatly trimmed garden hedge forms a mouth. You begin to ask yourself, are these faces happy or sad? Or maybe angry? You run them by your gut feeling, and with a rush of excitement you become aware.

1.1 Motivation and thesis question

This introductory story is a simple (and hopefully effective) way to describe the motivation behind the purpose of this thesis. The story could carry the scenario of your first time looking at cars at a car yard (presumably an exciting and unwary moment) or staring into the morning clouds at the beginning of the day, however, we are all familiar with the appearance of a house – a building that could be as simple as two windows and a door. Ask yourself, would the windows be the eyes? And what about the door? This ability to see a face where a face *does not* exist is a psychological phenomenon known as 'pareidolia'.

Returning to the initial story, and asking whether you can spot a face in the row of houses and the expressions they are making is not a challenging task. This is because seeing and evaluating faces is a natural ability in all of us[1]. My thesis question is asking whether a machine, an unnatural ubiquitous species, can see a face or a collection of faces in a scene where a face *does not* exist, and whether the machine is capable of assessing the expressions of these faces. In a simplified form, 'Can a machine describe the emotional response to a scene?'

After a quick ponder of my thesis question a veteran scientific reader would immediately be drawn to the literature relating to face detection and facial expression recognition, and the use of popular learning methods such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM). However, the reader should be aware that the research described in this literature aims to find *human* faces where a face *does* exist, and recognise *human* facial expressions. This effectively leaves a gap where the contributions to my thesis question belong.

1.2 The visual percept of pareidolia

Earlier I loosely introduced the term *pareidolia*, which is defined as the ability to perceive significance in random and vague stimuli. Our human body has a multitude of senses that can perceive a stimuli. We are all familiar with the senses of sight, hearing, taste, smell and touch. But did you know about other internal senses such as temperature, kinesthesia, pain, balance and acceleration? Pareidolia can arise through any of these senses. However, the visual percept of sight is the one most relevant to the topic of my thesis question, *scene perception*.

[1] to be technically correct, it is not absolutely *all of us*. I discuss this further in Chapter 2 'Cognitive science and Psychology literature'

1.3 But why faces? A cognitive science matter

As an example exercise, for a moment, let our eyes wonder around our surroundings and rest them on an unfamiliar area where everything is still. Ask yourself, is the scene vibrant and exciting? Or is it mundane and boring? Most importantly, are you able to describe *what* makes the scene vibrant? Or mundane? You begin formulating questions in your head and matching them to your *gut feeling* – it's the colour ... perhaps; it's the lines ... perhaps. These questions that we raise are all answered with conscious decisions. Could some of these awakening questions of your scene be answered by your *subconscious*? If so, what would they be? And *could a machine mimic this achievement*?

But why faces? My research in the literature of Cognitive Science (which I present in Chapter 2) shows that the brain looks for faces both at the conscious and subconscious levels. This roughly suggests that we are hard-wired to look for faces whether we like it or not, and the brain does so even when faces or minimal face-like patterns are not centred in our visual focus[2]. Then it is logical to assume that the face plays an important role in scene perception. This leads back to the example exercise of describing our scene. To some individuals, describing our *gut feeling* can be a daunting task – questions can lead to confusion rather than clarity. To have a *machine* that is capable of describing a scene allows the vagueness to become transparent – to become clear.

1.4 Contribution to Facial Expression Classification

Given a collection of perceived abstract faces from a scene, we could conclude that the definition of pareidolia has been satisfied. That is, we looked at the scene and we have drawn significance from random and vague images that a face is present, even though the face *does not* exist. However, I believe that the scene is significant as we are able to produce an emotional response to it, and that this emotion is drawn from facial expressions; hence returning to my thesis question. Hypothesising a formulated question from a Cognitive Scientist would be – 'If a face is processed by the brain, does the expression of the face get processed along with it? And if so, would an emotion be associated with it?'

In pursuing the second part of my thesis question, I present the literature

[2] the reference [176] is presented in Chapter 2

on the regions of the brain that process facial expressions and emotions, in Chapter 2. In Chapter 5, I present the literature on classifying facial expressions, as well as my findings of classifying facial expressions based on a holistic and component based approach. I also present my face model used to provide the best classification rate. My face model contains a set of feature points that are positioned across the eyes, mouth and brow, which were inserted manually into all the training data.

1.5 Contribution to Holistic Face Perception

Returning our focus to the veteran scientific reader, although the aims in the literature on face detection and facial expression papers are to find *human* faces and recognise *human* facial expressions, the question begs, 'Can they be used for finding *other* faces besides the human face?' and 'Are they able to recognise expressions other than *human* facial expressions?' To answer these questions I reviewed the literature.

My investigation into face detection papers shows that they have primarily been holistic based and they have shown to be performing very well. Although they are designed to detect human faces, they still produce false positives – meaning that the machine sees a *human* face where none exists. The logical idea is to exploit the false positives for my purpose. I found that this is possible using image preprocessing techniques such as edge detection. Consequently, I present my holistic based approach on *pareidolia* in Chapter 6.

1.6 Contribution to Component-based Face Perception

But is that enough? Are holistic based methods good enough for detecting faces for my purpose? Once again, let us return to our imagined house with the two windows and a door. When you envisioned it, where were the windows and the door located? Were their locations evocative of a *human* face? What would happen if we move the windows further away horizontally? Or move both windows vertically higher? Would you still consider this new arrangement to be a face? In my consideration I define it to be so, and this is where holistic based methods become less effective.

I present the literature on component based face detection in Chapter 7, and by doing so I also present my component based approach on *pareidolia*.

This method was designed to detect face-like patterns where the components such as the eyes and mouth are present. The main aim was for the machine to look for faces without the mindset of where the eyes and mouth would be with respect to the *human* faces in the training data.

1.7 Contribution to Support Vector Machines

I have purposely left the description of the learning method used last as I wanted to describe my motivation and my thesis question clearly. My literature review on face detection and facial expression recognition papers (as well as classification tasks in general) has shown that Support Vector Machines (SVM) are very capable when compared to many other learning methods. Consequently, I use SVMs in my experiments for analysing facial expressions and detecting faces.

Support Vector Machines are designed to solve two-class problems. This requires training data that includes both the *positive* and *negative* class. However, for face detection I use the One-Class SVM where only the *positive* class is present – creating a virtual negative space. This reflects the situation of the proposal that we are hard-wired to look for faces at birth – as some studies in the Cognitive Science literature suggest (see Chapter 2, ‘Cognitive Science and Psychology literature’).

My contribution to Support Vector Machines was made through my experiments in facial expression classification. At the time I wanted to show the classification rates of each pair of expressions (i.e. happy vs surprise, sad vs fear, ...) to find correlations between a machine’s capability and that of human participants in psychology studies. I wanted to compare the optimal expression pair classification performance of human and machine in order to have a ‘fair’ playing field. To find the optimised performance, I searched for the best parameters for each pair of expressions and used them for multiclass classification. As a consequence of taking this step, I realised that the standard multiclass Support Vector Machine does not do this – they have the same parameters for all the binary classifiers in their multiclass framework. To explore the significance of my approach I expanded my experiments involving real world datasets. The end result is a method I called ‘Pairwise Adaptive Support Vector Machine’ (*pa*-SVM), which is described and discussed in Chapter 4.

1.8 Exploring the grey area with the training data

In the journey to address my thesis question, I have designed my experiments to cover several considerations in the training data. This is because when we examine a dataset, we often ask ourselves 'Is the dataset too small?','Is there enough information present?','What about imbalanced data?' In some cases, these questions get convoluted with 'What normalisation should I use?' Perhaps one of the main questions that needs closure in the field of face detection and facial expression classification would be 'Is the image resolution optimal?' These considerations are important, as the outcome of a classification is influenced by what is contained in the training data and how it was prepared prior to the learning process. I linger on this issue as it is a grey area, and one that I have explored and discussed in this thesis.

1.9 Summary and overview of chapters

In this chapter, I introduced my motivation and my thesis question, 'Can a machine describe the emotional response to a scene?' Investigating this question led to more specific questions, 'How can a machine describe a scene?' and 'What features would it use?' A small amount of literature from Cognitive Science and Psychology was presented to support why I believe that *faces* and *facial expressions* would be useful features for scene perception. Then I described my contributions for analysing facial expressions and detecting faces using Support Vector Machines (SVM), followed by my contributions to SVM. The final section described the grey areas in the training data, which have not been fully discussed in the literature, and it is my intention to explore these issues in my experiments.

The remaining chapters of this thesis are laid out as follows:

- Chapter 2 presents further literature from Cognitive Science and Psychology that is relevant to the detection of faces and pareidolia. I explore the regions of the brain that are active for faces and facial expressions, followed by the brain regions for holistic and component based processing of faces. Next, several emotion models from relevant to the detection of faces and pareidolia. of basic emotions are presented along with my reasons for why I chose Ekman's *Universal Facial Expressions of Emotion* model. The chapter concludes with literature on the link between pareidolia and creativity and its application by neurologists for diagnosing neurological disorders.

- Chapter 3 presents the theory of soft margin Support Vector Machines and the relevant parameters used in practice. The C-SVM and ν-SVM are described using a two-class approach, followed by the different kernels for mapping data from input space to feature space – i.e. linear, polynomial and Gaussian kernel. Then One-Class SVMs are presented using the hyperplane and hypersphere approach. The chapter concludes with the frameworks of two-class classifiers for multiclass classification.

- Chapter 4 presents my Pairwise Adaptive Support Vector Machines (pa-SVM) which are a refined multiclass SVM. Real world datasets from the UCI Machine Learning Repository were used to show the significance of my method, which was originally conceived from my facial expression study.

- Chapter 5 presents Facial Expression Classification. This chapter explores and compares a holistic and component based approach to classifying facial expressions. Ekman's *Universal Facial Expressions of Emotion* are further discussed, and my face model, which is used in subsequent chapters, is presented.

- Chapter 6 presents Holistic Face Perception. The literature on traditional holistic approaches is presented here. I devised an empirical platform to evaluate the application of a holistic approach for perceiving faces in a scene. For the training data, I used my face model to create cartoon faces that are diffused into a number of minimal face-like patterns. Several preprocessing techniques were evaluated to show which is suitable for perceiving abstract faces holistically, and for the classification of expressions.

- Chapter 7 presents Component Based Face Perception. A separate chapter was required to show the distinctions when compared to a holistic approach. The literature on component based approaches is presented here. Because the existing methods available do not meet my requirements for a suitable component face detector I developed a new method. In this chapter, I show the potential of the possible faces that can be perceived with my component face detector, and evaluate the performance of classifying expression using face components (i.e. brows, eyes and mouth). Once again, my face model was used to extract face components from the cartoon face dataset used in the previous chapter.

- Chapter 8 presents the final argument of my thesis question – its relevance and the contributions that were made in pursuing my thesis question. My final words introduce my last question, 'What is the next step?'

You may notice that this introduction presented Support Vector Machines last, however it was necessary to put the chapters on Support Vector Machines early as they are referred to in the remaining chapters.

1.10 Publications

The following publications have been written and submitted within the timescale of this thesis.

Journals

- Kenny Hong, Stephan K. Chalup, and Robert A.R. King. Affective Scene Perception using Machine Pareidolia of Facial Expressions. Manuscript under Review.
- Stephan K. Chalup, Kenny Hong, and Michael J. Ostwald. Simulating pareidolia of faces for architectural image analysis. International Journal of Computer Information Systems and Industrial Management Applications (IJCISIM), 2:262–278, 2010.

Conference Proceedings

- Kenny Hong, Stephan K. Chalup, Robert A.R. King, and Michael J. Ostwald. Scene perception using pareidolia of faces and expressions of emotion. In IEEE Symposium on Computational Intelligence for Creativity and Affective Computing (CICAC), 2013. Manuscript accepted for publication.
- Kenny Hong, Stephan K. Chalup, and Robert A.R. King. A component based approach for classifying the seven universal facial expressions of emotion. In IEEE Symposium on Computational Intelligence for Creativity and Affective Computing (CICAC), 2013. Manuscript accepted for publication.

- Aaron S.W. Wong, Steven Nicklin, Kenny Hong, Stephan K. Chalup, and Peter Walla. Robot emotions generated and modulated by visual features of the environment. In IEEE Symposium on Computational Intelligence for Creativity and Affective Computing (CICAC), 2013. Manuscript accepted for publication.

- Kenny Hong, Stephan K. Chalup, and Robert A.R. King. An experimental evaluation of pairwise adaptive support vector machines. In The 2012 International Joint Conference on Neural Networks (IJCNN), pages 1–8, 2012.

- Kenny Hong, Stephan K. Chalup, and Robert A.R. King. A component based approach improves classification of discrete facial expressions over a holistic approach. In 2010 International Joint Conference on Neural Networks (IJCNN 2010), pages 90–97. IEEE, 2010.

- Stephan K. Chalup, Kenny Hong, and Michael J. Ostwald. A face-house paradigm for architectural scene analysis. In Richard Chbeir, Youakim Badr, Ajith Abraham, Dominique Laurent, and Fernando Ferri, editors, CSTST 2008: Proceedings of The Fifth International Conference on Soft Computing as Transdisciplinary Science and Technology, pages 397–403. ACM, 2008.

Chapter 2

Cognitive Science and Psychology Literature

Contents

In the previous chapter I presented my thesis question 'Can a machine describe the emotional response to a scene using perceived faces and facial expressions?' Following this, I lightly touched on the reasons why faces and their expressions should be used, and I emphasised that the significance of a scene goes beyond the perception of faces from random and vague images contained within it. I propose that the significance of a scene is the result of our emotional response to it – and this emotion is drawn from the facial expressions of perceived faces.

In this chapter I review the literature from Cognitive Science and Psychology to support my thesis question as to why faces (and their expressions) are significant for scene perception. On the Cognitive Science side, I begin by establishing the regions of our brain that are active for faces and facial expressions and scenes, followed by why the subconscious processes of these regions are more relevant to my thesis question than are the conscious processes of face perception. I then present the regions of the brain involved in holistic and component based processing of faces. Finally, I present the literature that suggests that faces can be perceived in minimal face-like patterns even when they are not centred in our visual focus; followed by the region of the brain which ranks the likeness of face patterns to genuine faces. On the Psychology side, I present the literature on basic emotions and the reasons for why I chose the Universal Facial Expressions of Emotion as my emotional model. This chapter concludes with a discussion of the literature on the link between pareidolia and creativity and its application by neurologists in diagnosing neurological disorders.

2.1 Regions of the brain that are active for the processing of faces and facial expressions – and scenes

The human brain is a powerful cognitive machine, which continuously processes signals from numerous stimuli. My first question (relevant to my thesis topic) is 'Are there specific areas of the brain that are active for faces and facial expressions?' From the literature review, I discovered that cognitive neuroscientists have used a variety of methods to answer this question. One of their main methods is functional Magnetic Resonance Imaging (fMRI). This technique is useful in revealing the neural pathways of the brain, and from their studies they have isolated the main regions of the brain involved in the processes relevant to face perception, facial expression processing and scene perception. These regions are – the inferior occipital and fusiform gyri (responsible for face perception), and the amygdala (which is responsible for processing emotions); they lie close to each other as shown in Figure 2.1. The figure also shows the parahippocampal gyrus – a study has used functional magnetic resonance imaging (fMRI) to show that this region is active for processing scenes [55]. A supporting study that analysed fMRI results of brain regions during viewing of emotional scenes and emotional faces shows that the activation of the amygdala has the greatest overlap [187], and the activation is stronger for facial expressions than for scenes [86, 195]. In subsequent sections I further discuss the three regions (the inferior occipital and fusiform gyri and the amygdala) involved in the processing of faces and facial expressions.

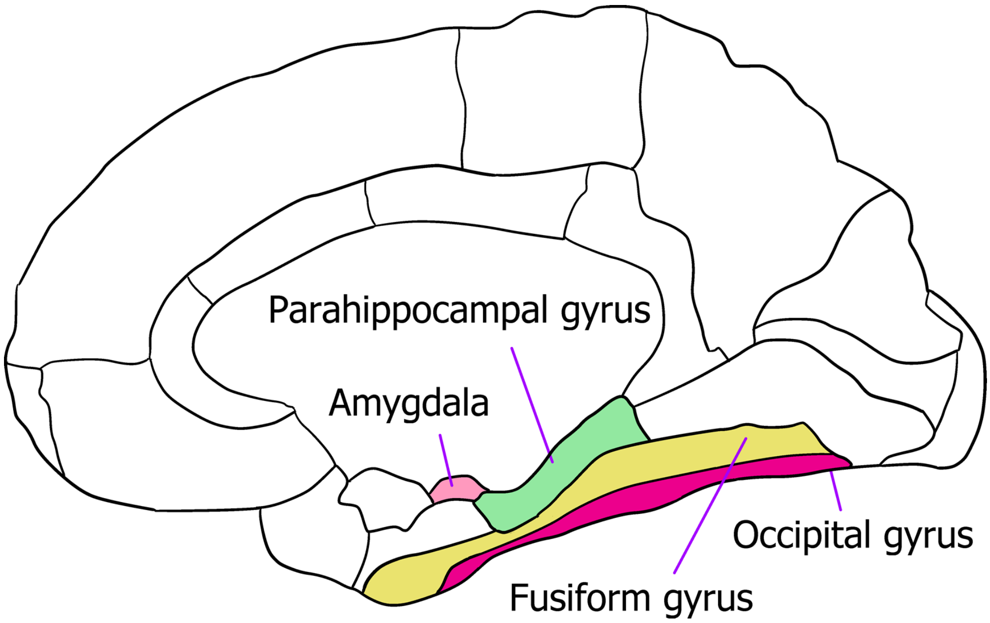

Figure 2.1: The regions of the brain that are active for faces and facial expressions – and scenes. Each region has its own responsibilities. The inferior occipital and fusiform gyri are responsible for face perception, the amygdala is responsible for processing emotions, and the parahippocampal gyrus is responsible for scene perception. This illustration is based on images from [22, 156].

2.2 How does the subconscious relate to my thesis question

Before I dive into the specifics of these brain regions and their activation by faces and facial expressions, I want the reader to bear in mind the meaning of the *subconscious* and how it plays into my thesis question.

Lets visualise our subconscious to be a pool of knowledge, which perpetually gathers information from various stimuli in our surrounding environment. Our pool is weirdly shaped, with varying depths at the bottom and overflowing at the edge. The information that overflows is lost and can no longer be retrieved. I denote this loss to be the unconscious, which is the extreme state of the subconscious. A slow moving water wheel hovers around this pool and each time it dips into the pool's surface the information is carried to our conscious, however to get information from the bottom requires specialised methods.

The slow moving water wheel contrasts to the rapid flow of information into this pool. It is this speed that many researchers have used as one of the main cues to when a subconscious process has occurred [84, 112]. You ask, 'How does this relate to my thesis question?' When we perceive a scene, we may lack the ability to fully describe our emotional response to it as the answers in our conscious mind are limited by our ability to question our subconscious. The rapid rate at which the subconscious is processed means that it is rich in information, and the ability for a machine to relay this information allows our emotional response to a scene to become transparent – to become clear.

2.3 How our brain regions subconsciously process faces and facial expressions

From this understanding of the subconscious, 'How do our brain regions subconsciously process faces and facial expressions?' In the literature review I found that faces are processed subconsciously by the early activation of the inferior occipital and fusiform gyri (using magnetoencephalography (MEG) readings) when human subjects are presented with images of objects, faces and face-like objects (i.e. *pareidolia*) [84], and this rapid activation is seen across the subcortical pathway. The rapid activation of this subcortical pathway has been linked to the activation of the amygdala, which have been shown to be involved in the processing of emotions from facial expressions both in newborns [112] and adults [2, 191, 199] (for further reading [187, 202]). In particular, it is the right amygdala which is more involved in a subconscious process while the left amygdala is more involved in a conscious process [162]. The study of newborns recognising faces and facial expressions [112] implies that the brain may be hard-wired to look for faces from birth, and the use of schematic face-like patterns in the study suggests that newborns are capable of perceiving faces from minimal face-like patterns (once again, *pareidolia*). The short and direct path of the subcortical face route is viewed by some as the 'low-road', while others believe that the subconscious decoding of faces and emotions from facial expressions uses ‘many-roads’ [7] such as cortical-cortical and cortical-subcortical functional connectivity [162].

2.4 Distinct brain regions for holistic and component based processing of faces

I have now established that there are brain regions that are active for subconsciously processing faces and facial expressions – this being the inferior occipital and fusiform gyri for face perception and the amygdala for processing of emotions. Because of my curiosity, I questioned why there are two brain regions required for face perception. However, before I go any further (and to be technically in line with the neuroscience terminology), the specific region of the fusiform gyrus for processing faces is known by cognitive neuroscientists as the ‘fusiform face area (FFA)’ and the specific region of the inferior occipital gyrus for processing faces is known as the ‘occipital face area (OFA)’ [70].

Returning to my curiosity, the question is ‘Do the occipital face area (OFA) and fusiform face area (FFA) have specific roles for processing faces?’ There have been many studies that have shown the FFA processes faces holistically [234] and argue that it is also sensitive to face components [6, 108]. Further studies have supported the theory of the FFA processing faces holistically [234] (using fMRI with multi-voxel pattern analysis). However, it is the OFA that is more sensitive to processing face components [6] (using fMRI with blood-oxygen-level dependence responses). In addition, the OFA has been shown to give preference to face components, primarily the eyes, followed by the mouth and then the nose [6]. There are debates as to whether a hierarchical order between the OFA and FFA exists – currently a more complex interplay between the OFA and FFA is assumed [7].

2.5 Faces can be perceived beyond the center of our visual focus and face semblance is ranked automatically

The distinction between the brain regions involved in processing faces by components and holistically were important considerations when I approached my thesis question in relation to face detection methods for my machine. Pareidolia is an instance of seeing a face by the sum of its parts, but is it correct to assume that these parts have to be centred in our visual focus? A study using noisy images and fMRI suggest that faces can be perceived with minimal face-like patterns even when these features are not centred in our visual focus [176]. In addition, the ranking of face likeness (from images unlike faces to genuine face images) has been shown to engage the left fusiform face area (FFA), then categorical face/non-face judgements occur on the right [148]. These findings have a direct influence on the realisation of how my machine would rank perceived faces as meaningful. The ability of seeing faces that are not centred in our visual focus means that a machine should perceive faces in different areas of an image. Similar to how the left fusiform would rank the face likeness to that of a genuine face, I foresee my machine would replicate this phenomena using machine learning techniques.

2.6 Which set of emotions and facial expressions to consider?

So far I have presented the literature to establish the regions of the brain that are active for faces and facial expressions, and how the brain can perceive faces beyond the centre of our visual focus and ranks their likeness to genuine faces automatically. I return the reader to my thesis question – I have described that it is not just the perceived faces that are significant in a scene, but the emotion produced from them. I have presented relevant studies that show that the brain region known as the amygdala is responsible for processing emotions and is activated by faces and facial expressions. The important question here is, 'Which set of emotions and facial expressions to consider?'

From the literature review, there are four prominent theories of basic emotions, and the advocates of each have presented their arguments to the relevance of their emotional model – Ekman and Cordaro [53]; Izard [106]; Levenson [126]; and Panksepp and Watt [161]. The similarities and differences of each theorist are presented and discussed by Tracy and Randles [208]. Examining each of the emotional models described, I find that Ekman and Cordaro's model is the most relevant for my thesis question. This is because I believe that the emotions of Interest/Seeking (Izard, Levenson, and Panksepp and Watt), Lust/Love (Panksepp and Watt, and Levenson), Care/Relief (Panksepp and Watt, and Levenson), and Pride (Tracy and Randles) are difficult to recognise through facial expressions, when compared to Ekman and Cordaro's model of the seven emotions – Happy, Sad, Fear, Anger, Disgust, Contempt and Sur-