Journal of Language, Technology & Entrepreneurship in Africa (JOLTE)
Vol. 12 No. 2 2021

A Comparative Emotions-detection Review for Non-intrusive Vision-Based Facial Expression Recognition

Khushi Gupta
Sam Houston State University
khushigupta2172@gmail.com

Leah Mutanu
United States International University-Africa
lmutanu@usiu.ac.ke

Jeet Gohil
United States International University-Africa
Jeetg57@gmail.com

Abstract
Affective computing advocates for the development of systems and devices that can recognize, interpret, process, and simulate human emotion. In computing, the field seeks to enhance the user experience by finding less intrusive automated solutions. However, initiatives in this area focus on solitary emotions that limit the scalability of the approaches. Further reviews conducted in this area have also focused on solitary emotions, presenting challenges to future researchers when adopting these recommendations. This review aims at highlighting gaps in the application areas of Facial Expression Recognition Techniques by conducting a comparative analysis of various emotion detection datasets, algorithms, and results provided in existing studies. The systematic review adopted the PRISMA model and analyzed eighty-three publications. Findings from the review show that different emotions call for different Facial Expression Recognition techniques, which should be analyzed when conducting Facial Expression Recognition.

Keywords: Facial Expression Recognition, Emotion Detection, Image Processing, Computer Vision

1. Introduction

As technology advances, users are finding themselves increasingly interacting with computers to accomplish various activities in their daily lives. For instance, a user will check their daily schedule on a digital device, order groceries online, swipe a card to access public transport and make payment transactions. This highlights the need to enhance human-computer interactions by integrating components that enable the machine to communicate and understand humans. Users often communicate with each other using various nonverbal signals such as hand gestures or facial expressions, which can enhance computer communication. Additionally, in a bid to make technology, more inclusive, application developers are increasingly becoming aware of the need to develop products accessible to people with disabilities. By providing alternative communication avenues, such users can easily use digital technology.

This study examines Facial Expression Recognition (FER) as a non-intrusive vision-based technique useful for automated emotion detection. This field is useful for enhancing human-computer interactions where machines can communicate and understand humans (Liliana & Basaruddin, 2018). However previous reviews in this area (Mellouk & Handouzi, 2020) point out that despite the potential of FER, existing reviews have only focused on some basic emotions (anger, contempt, Disgust, Fear, Happiness, Sadness, Surprise). This approach conflicts with what is present in everyday life, which has emotions that are more complex (Liliana & Basaruddin, 2018). In this respect, existing reviews have reported popular FER Algorithms as Convolutional Neural Networks (CNN) (Balasubramanian et al., 2019; Baskar & Gireesh Kumar, 2018; Kartali et al., 2018; S. Li & Deng, 2020) and Support Vector Machines (SVM) (Fathima & Vaidehi, 2020). Further research is required to investigate whether these algorithms work best for different emotions. For instance, Facial expression-based methods also offer an effective technique, frequently used by medical experts to detect the emotional patterns of autistic children (Ray et al., 2019).

Eye-tracking is fast in becoming one of the most used sensor modalities in affective computing recently for monitoring Fatigue emotion. However, many studies conduct experiments using physiological signals, such as EEG brainwave signals, pupil responses, electrooculography (EOG), electrocardiogram (ECG), electromyogram (EMG), as well as galvanic skin response (GSR). Non-contact approaches that make use of vision-based FER methods would enhance the user experience. The eye-tracker used for such experiments also detects additional information such as blink frequency and pupil diameter changes (Lim et al., 2020). A typical eye-tracker (such as Video Oculography) consists of a video camera that records the movements of the eyes and a computer that saves and analyses the gaze data (Klaib et al., 2021). The monitoring of Fatigue differs from the monitoring of basic facial emotions (such as Anger, or Happiness) because different facial aspects are monitored such as the percentage eye closure (PERCLOS), or head nodding, head orientation, eye blink, speed, gaze direction, saccadic movement, or eye color. This is in contrast to the basic emotions (we shall refer to them as the *Classic* FER emotions in this study) which call for monitoring of the eye corner, lip corner, mouth, eyebrow, eye-opening, mouth opening, eyebrow constriction, mouth corners displacement, mouth length, and nose-side wrinkles detection. (Liliana & Basaruddin, 2018).

By focusing on solitary emotion detection, existing reviews in FER studies do not illustrate how FER approaches vary based on the emotion detected. Aspects such as the types of datasets used, Choice of Feature Extraction and Emotion Detection Algorithms, Solution Design, and the Accuracy levels of results would inform future FER studies. Although various gaps have been highlighted by these reviews such as the inability of the solutions to handle pose (Bhattacharya & Gupta, 2019), image lighting (Jonathan et al., 2018), and the number of datasets used (Jonathan et al., 2018), without a comparative study it becomes difficult to appreciate whether this cuts across all types of emotions. Additionally, in many FER studies, the environment context seems to be ignored (Canedo & Neves, 2019). To address this, the current study set out to conduct a comparative analysis of popular emotions detected using vision-based FER techniques. The review process was started by identifying similar views in this area. These reviews highlighted the absence of literature on how the type of emotion detected influences the FER techniques used. The current review, therefore, set out to explore how the choice of datasets used, Feature Extraction approaches, Emotion Detection Algorithms, and the accuracy of the results are influenced by the emotion detected during automated non-intrusive Facial Expression Recognition.

2. Review of related work

The review papers selected focused on facial emotion recognition as illustrated by the infographic on the paper's keywords in Figure 1. The review papers were therefore adequate in revealing the extent and gaps in current FER reviews.

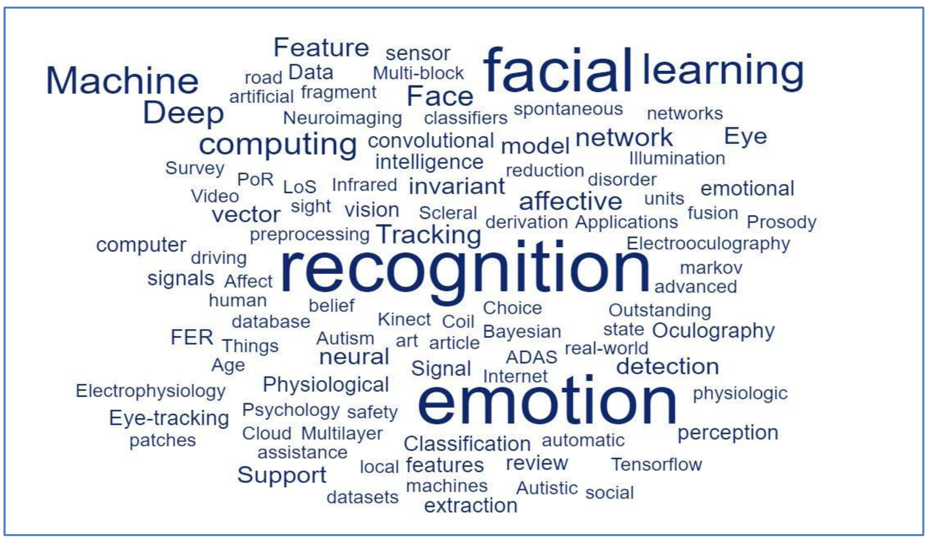
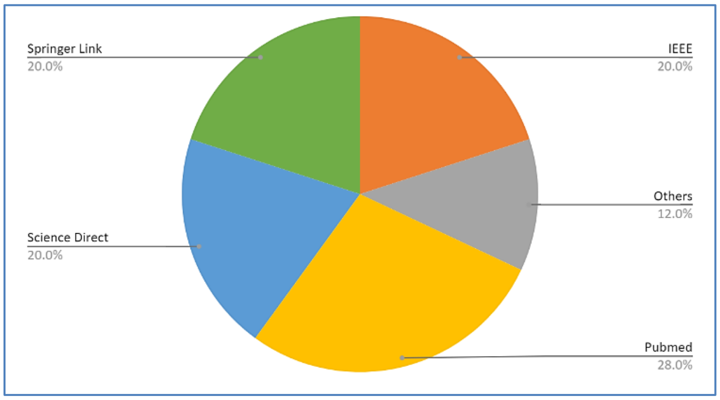
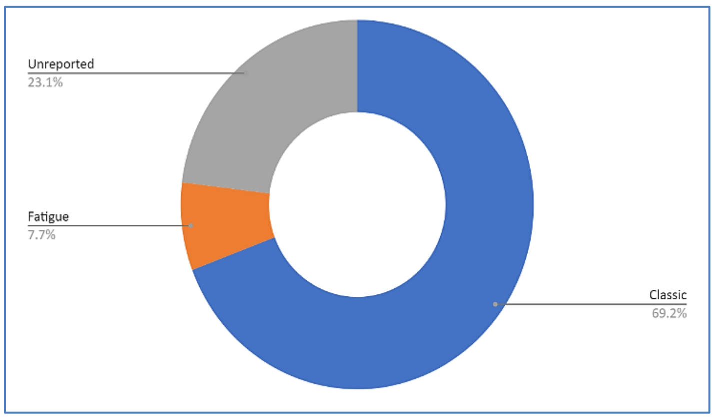


Figure 1. Word Cloud of the Review paper keywords

This study came across Twenty-Seven (27) review papers that focus on FER, mined from various datasets as shown in Figure 2 (a). The datasets used to mine the review articles included IEEE, Springer, PubMed, and Science Direct as illustrated. The results show that the distribution of review papers in the datasets is similar, attributed to the fact that Emotion recognition is a study that spans multiple disciplines, and therefore publications in this area cut across different datasets. Further analysis revealed that the reviews largely focused on the classic emotions (57.7%), with only eight percent (7.7%) looking at fatigue while the rest (34.6%) did not report the emotion they classified as shown in Figure 2 (b). Previous reviews have therefore not explored other emotions when analyzing research on FER. Few did provide limited analysis of different emotions and highlighted how FER approaches differ across different emotion studies. The findings of these reviews motivated the current review, which seeks to provide insights on how the type of emotion detected will influence the FER techniques used.



(a) Database Sources



(b) Emotions Examined

Figure 2. Review paper sources and emotions examined

Table 1. Number of papers used in existing reviews

References	**No. of Review Papers**	**No. Of Papers Used**
(H. Ashraf et al., 2018; Edwards et al., 2002; Jonathan et al., 2018; Michel & El Kaliouby, 2003)	4	< 50
(Canedo & Neves, 2019; Klaib et al., 2021)	2	>100
(Balasubramanian et al., 2019; Baskar & Gireesh Kumar, 2018; Bhattacharya & Gupta, 2019; Chengeta, 2019; Dzedzickis et al., 2020; Egger et al., 2019; Fathima & Vaidehi, 2020; Gantayat & Lenka, 2021; Harms et al., 2010; Kartali et al., 2018; M. Q. Khan & Lee, 2019; S. Li & Deng, 2020; Liliana &	20	Unreported

Basaruddin, 2018; Lim et al., 2020; Mellouk & Handouzi, 2020; Ray et al., 2019; Sabu & Mathai, 2015; Samadiani et al., 2019; Shu et al., 2018; Wagh & Vasanth, 2019; J. Zhang et al., 2020)

Most of the reviews did not report the number of papers used as observed in Table 1. Four reviews used less than fifty papers (Adeshina et al., 2009; H. Ashraf et al., 2018; Edwards et al., 2002; Jonathan et al., 2018) and only two reviews (Canedo & Neves, 2019; Klaib et al., 2021) used more than one hundred papers. Most of the reviews occurred in the last three years as shown in Figure 3 highlighting the growing interest in this area.

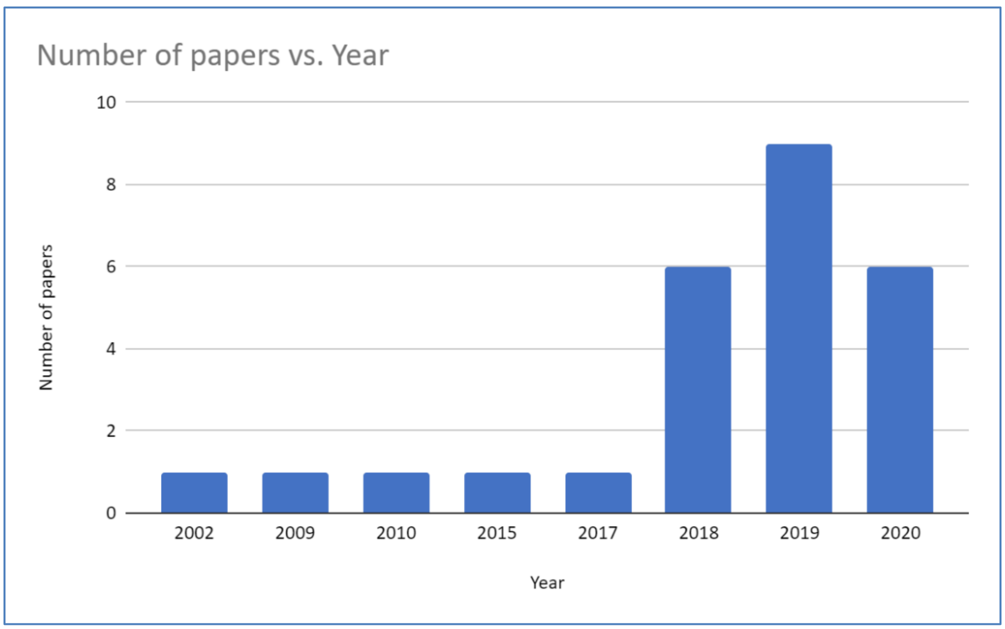
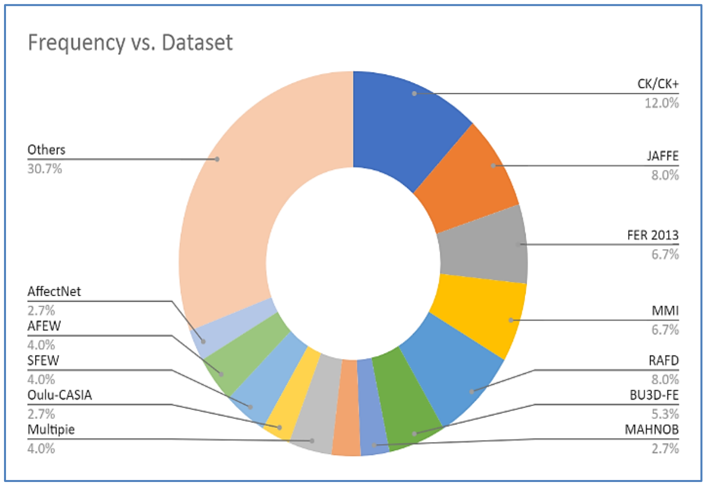
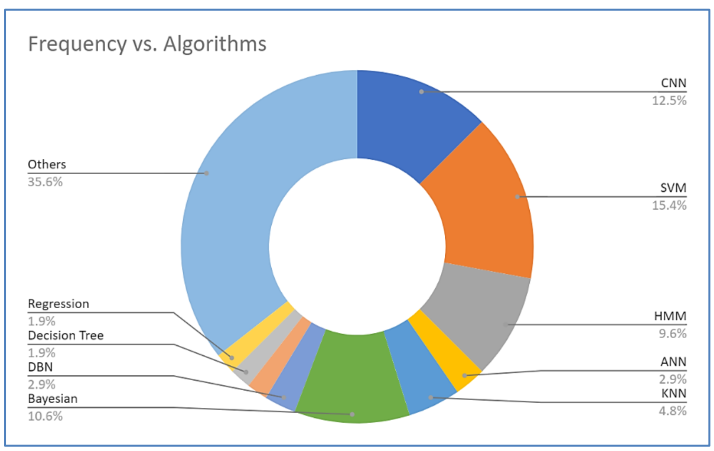


Figure 3. Review papers year of publication

The review papers revealed that CK/CK+ was the most popular publicly available dataset (Gupta, 2018; Mehendale, 2020; Mohammadpour et al., 2017; J.-M. Sun et al., 2008) used for FER as shown in Figure 4 (a). The "other" category includes datasets only used by individual papers. Examples of such datasets are the Karolinska Directed Emotional Faces (KDEF) (Canedo & Neves, 2019), Toronto Faces Dataset (S. Li & Deng, 2020), and the Geneva Multimodal Emotion Portrayals (GEMEP) (Mellouk & Handouzi, 2020) among others. The most popular algorithms used for classification are SVM and CNN as revealed by the reviews in Figure 4 (b) (H. Ashraf et al., 2018; Balasubramanian et al., 2019; Baskar & Gireesh Kumar, 2018; Bhattacharya & Gupta, 2019; Dzedzickis et al., 2020; Egger et al., 2019; Fathima & Vaidehi, 2020; Jonathan et al., 2018; Klaib et al., 2021; S. Li & Deng, 2020; Liliana & Basaruddin, 2018; Lim et al., 2020; Mellouk & Handouzi, 2020; Samadiani et al., 2019; Shu et al., 2018; Wagh & Vasanth, 2019; J. Zhang et al., 2020). The "other" category includes algorithms only used by individual papers such as Fuzzy expert systems (M. Q. Khan & Lee, 2019), Feedforward neural network (Fathima & Vaidehi, 2020), Independent component analysis (J. Zhang et al., 2020), and Gaussian mixture modeling (Canedo & Neves, 2019) among others.



(a) Datasets



(b) Algorithms

Figure 4. Review paper datasets and Algorithms

Based on the classic emotions, most reviews recommended the applications of FER for enhancing Human-Computer Interaction through affective computing (Adeshina et al., 2009; Balasubramanian et al., 2019; Canedo & Neves, 2019; Jonathan et al., 2018; Liliana & Basaruddin, 2018; Lim et al., 2020; Sabu & Mathai, 2015; Samadiani et al., 2019). Some reviews recommended additional application areas such as Road Safety for detection of driver fatigue detection (M. Q. Khan & Lee, 2019); Healthcare for Autism or Adverse Behaviour detection (Bhattacharya & Gupta, 2019; Edwards et al., 2002; Mohammadpour et al., 2017; Ray et al., 2019); Education for eLearning adaptive systems (Baskar & Gireesh Kumar, 2018; Klaib et al., 2021); and security for surveillance cameras or lie detection (Fathima & Vaidehi, 2020) as depicted in Figure 5.

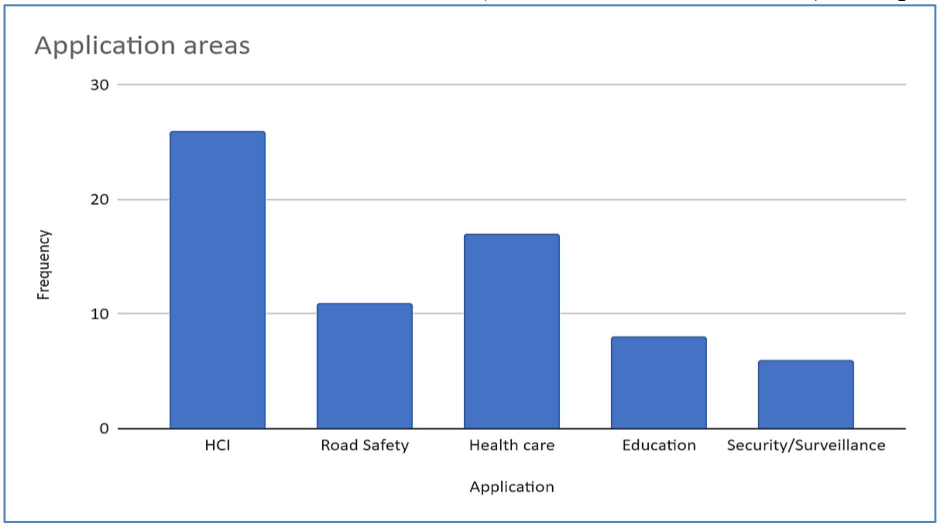


Figure 5. Recommended FER application Areas

3. Methodology

3.1 Research Process

The process started, by mining relevant studies through database searches. A systematic review of the literature was conducted using online databases that index health and technology research namely: IEEE, Science Direct, ACM Digital Library, and Springer during the period 2000 to 2021. The review process made use of the PRISMA methodology (P.R.I.S.M.A, 2015) for reporting the systematic reviews and meta-analyses. The search keywords used were facial expression detection, digital eye strain, and fatigue detection. To enhance the search process, acronyms complimented some of the keywords, for example in place of expression and digital we used terms such as emotion and computer respectively. Due to the different formats of each database, we used slightly different expressions of our search strategy for each database. For example, Table 2 displays the search strategy for the PubMed database.

Table 2. Mining Strategy used for PubMed Database

Detection	**AND**	**Digital**	**AND**	**Fatigue**	**AND**	**Machine learning**	**NEAR**	**Computer Vision** **Camera**

We reviewed relevant articles published in the past 21 years (2000 -2021). The timeframe indicates when FER technology started and when it started gaining popularity which is 2010. Only papers in English were included in the review process. The search criteria sought articles that involved fatigue detection. Generic search terms (according to the thesaurus of each database) identified the relevant studies. The process of screening relevant studies used the inclusion and exclusion criteria tabulated in Table 3. The identification and elimination of duplicate studies followed. We categorized papers having the same titles or published by the same author on the same subject as duplicates.

Table 3. Paper Mining Inclusion and Exclusion Criteria

Exclusion Criteria	**Inclusion Criteria**
The technology used for the detection of fatigue or emotions e.g., using EEG signals to monitor fatigue.	Machine learning for measurement of fatigue
Research not Published in English	Monitoring of classic emotions
Research Published before 2000	Monitoring of fatigue
Research-based on monitoring parameters. Body postures for fatigue	Peer-Reviewed publications
Papers that were not considered original research, such as letters to the editor, comments, etc.	Been published in English

3.2 Population and Sampling

Initially, the search yielded 134 articles overall (IEEE = 50, Science Direct = 20, PubMed = 10, ACM Digital Library = 13, Springer = 16 and others = 25). After excluding duplicated papers, 121 records were eligible for screening. Twenty papers (20) that did not meet our inclusion criteria based on the initial screening resulted in 114 studies evaluated for eligibility. The authors retrieved and reviewed full-text records. After excluding irrelevant studies, eighty-three (83) papers remained as the population of the study. The authors sampled the entire population. The study selection process is depicted in Figure. 6.

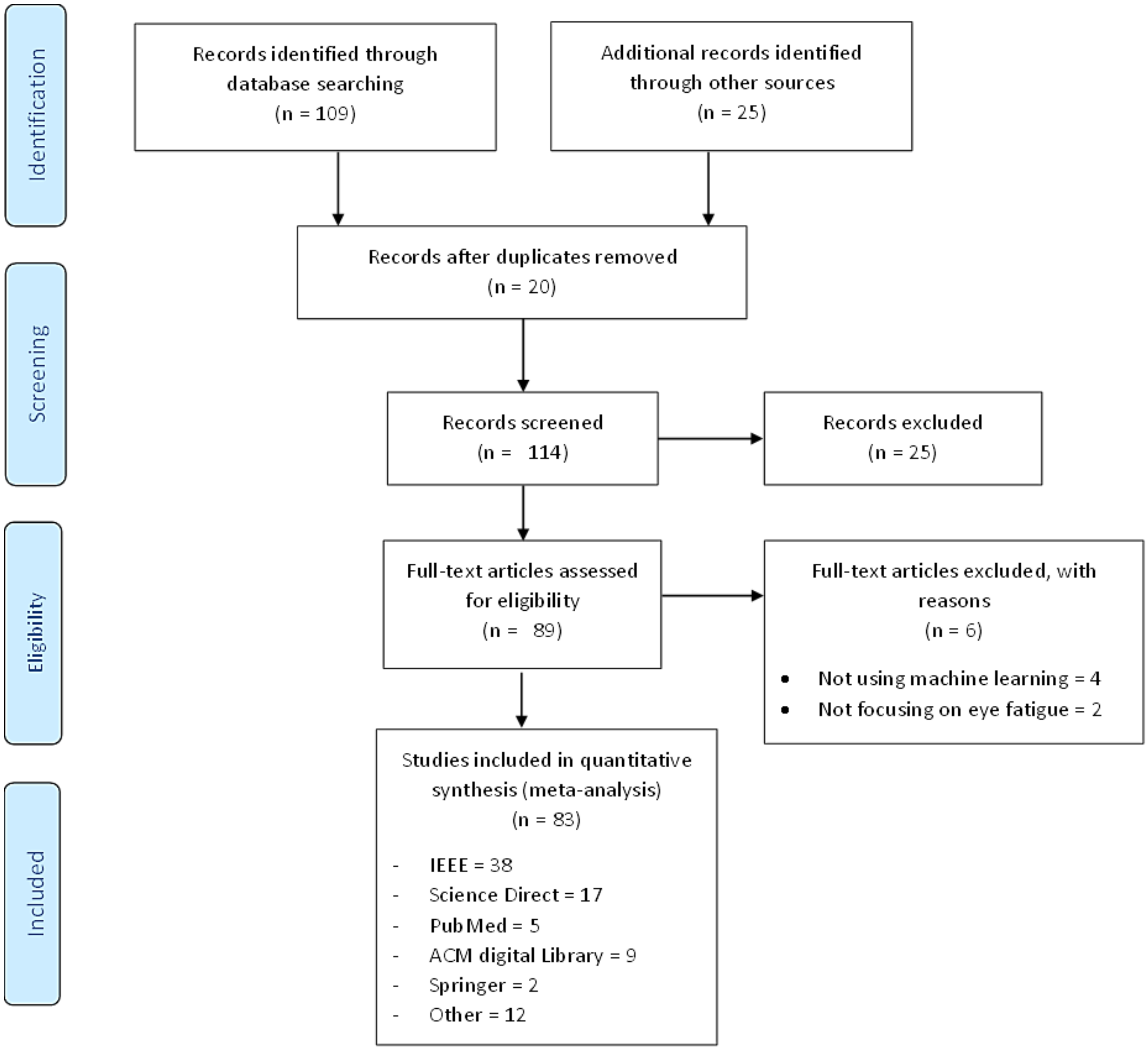


Figure 6. Paper Selection Process

3.3 Data Collection

This final review made use of 83 papers sourced from IEEE, Science Direct, ACM Digital Library, and Springer as shown in Figure 7. The list of papers extracted from each database is listed in Table 4. This review used 51 papers representing fatigue emotion and 29 papers representing classic emotions.

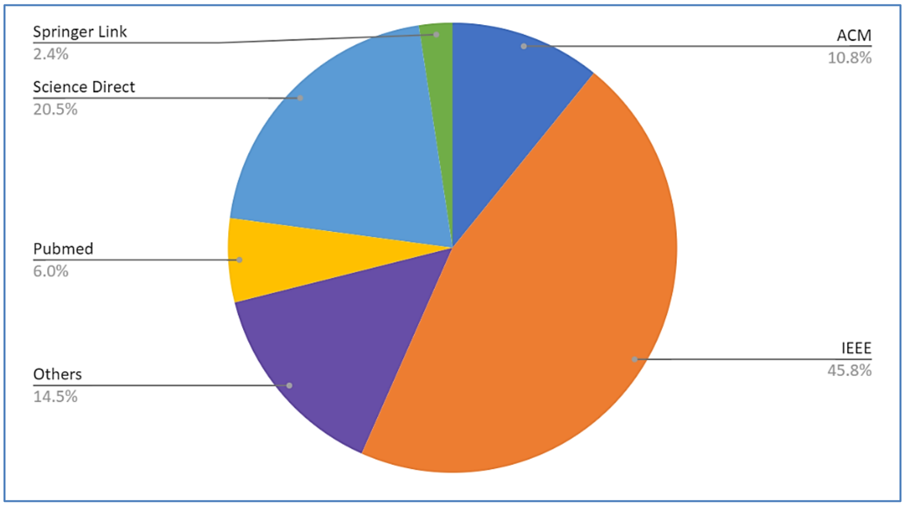


Figure 7. Sources of Papers used for the review

Table 4. Paper Mining Inclusion and Exclusion Criteria

Emotion	**Database**	**Papers Used**
Fatigue	ACM, IEEE, Pubmed, Science Direct, Others	(Dagar et al., 2016; Deshmukh et al., 2017; Gan, 2018; Ghandi et al., 2010; Gilda et al., 2017; Guo et al., 2018; Gupta, 2018; Hickson et al., 2019; Ithaya Rani & Muneeswaran, 2016; Ivanova & Borzunov, 2020; Jing et al., 2020; Le & Vea, 2016; Loob et al., 2017; Miyakoshi & Kato, 2011; Mohammadpour et al., 2017, 2017; Park et al., 2015; Rajesh & Naveenkumar, 2016; Rakhmatulin & Duchowski, 2020; Ramdhani et al., 2018; Sebe et al., 2007; S. Singh & Nasoz, 2020; J.-M. Sun et al., 2008; X. Wang et al., 2018; Xiaoxi et al., 2017; L. Zhang et al., 2013; Z. Zhang et al., 2016)
Classic Emotions	ACM, IEEE, Pubmed, Science Direct, Springer Link, Others	(Abdulin & Komogortsev, 2015; Bin et al., 2019; Chang & Chen, 2014; Chen, 2017, 2017; Coetzer & Hancke, 2011; Cyganek & Gruszczyński, 2014; Ed-doughmi & Idrissi, 2019; Fa-deng & Min-xian, 2010; Gao & Wang, 2017; Huang et al., 2018; Huang & Wang, 2019; Iatsun et al., 2015; Jie et al., 2010; Jing et al., 2020; M. I. Khan & Mansoor, 2008; Kim & Lee, 2020; Knapik & Cyganek, 2019; Krestinskaya & James, 2017; Kurylyak et al., 2012; F. Li et al., 2020; K. Li et al., 2019; L. Li et al., 2011; X. Li et al., 2015, 2015; Z. Li & Nianqiang, 2019; Lin et al., 2015; Z. Liu et al., 2020, p.; Maior et al., 2020; McKinley

	et al., 2011; Nie et al., 2017; Rakhmatulin & Duchowski, 2020; Rehman et al., 2018; Shahrabi Farahani et al., 2013; Sharan et al., 2019; H. Singh et al., 2011; Song et al., 2020; Sravan et al., 2018; X. Sun et al., 2017; Tang et al., 2010; F. Wang et al., 2020; Y. Wang et al., 2019; Xie et al., 2012; Xing et al., 2019; J. Xu et al., 2018; X.-W. Xu et al., 2020; F. Zhang et al., 2017; Zheng et al., 2016; Zhuang et al., 2020)

Research in FER has steadily increased over the years showing the growing interest in this area. The results in Figure 8 depict 2010 as the onset of this interest with the highest number of studies conducted in 2019 (Ed-doughmi & Idrissi, 2019; Huang & Wang, 2019; Knapik & Cyganek, 2019; Xing et al., 2019) and 2020 (F. Li et al., 2020; Song et al., 2020; Zhuang et al., 2020).

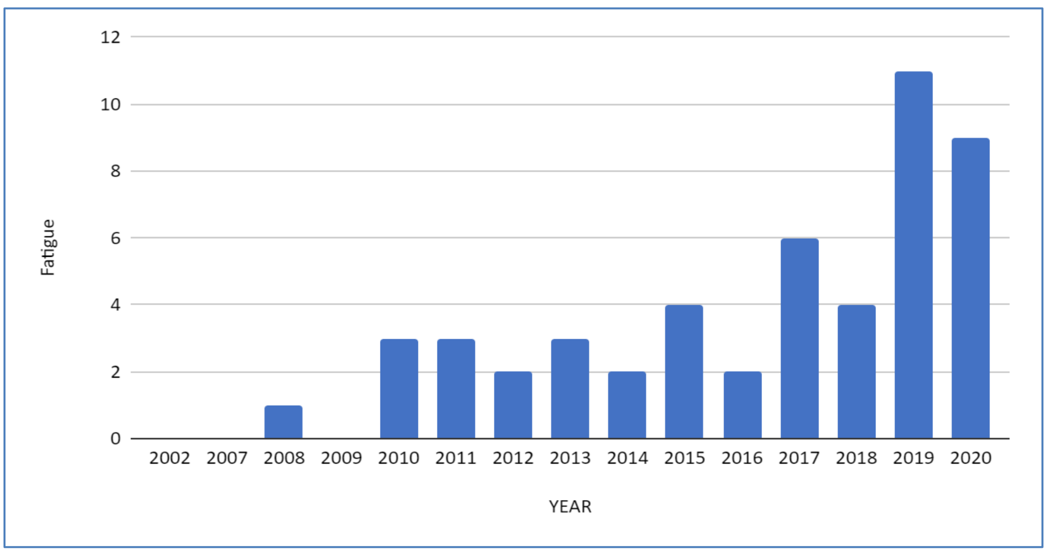


Figure 8. Progress of FER Studies over the years

This review identified papers that focus on the detection of emotions using Automated Facial Expression Recognition techniques. It aimed at revealing the extent to which existing studies have explored the subject, drew analogies, and proposed solutions to research gaps in this area. The research emphasized studies that do not focus on the popular classic Facial Expression Emotions (Happy, Sad, Angry, Fear, and Normal) such as those focusing on Fatigue (Chen, 2017; Ed-doughmi & Idrissi, 2019; Huang et al., 2018; Huang & Wang, 2019; Kurylyak et al., 2012; H. Singh et al., 2011; Sravan et al., 2018; X. Sun et al., 2017; Xing et al., 2019), Pain (A. B. Ashraf et al., 2009) or Digital Eye Strain to highlight these gaps. The word cloud generated from the papers' keywords in Figure 9, illustrates the relevance of the selected papers. The results show that the selected papers focused on the automated detection or recognition of fatigue on the face or eyes using algorithms such as PERCLOS, SVM, and CNN for drivers. The findings also reveal that outside the classic emotions, FER studies have so far largely focused on Fatigue.

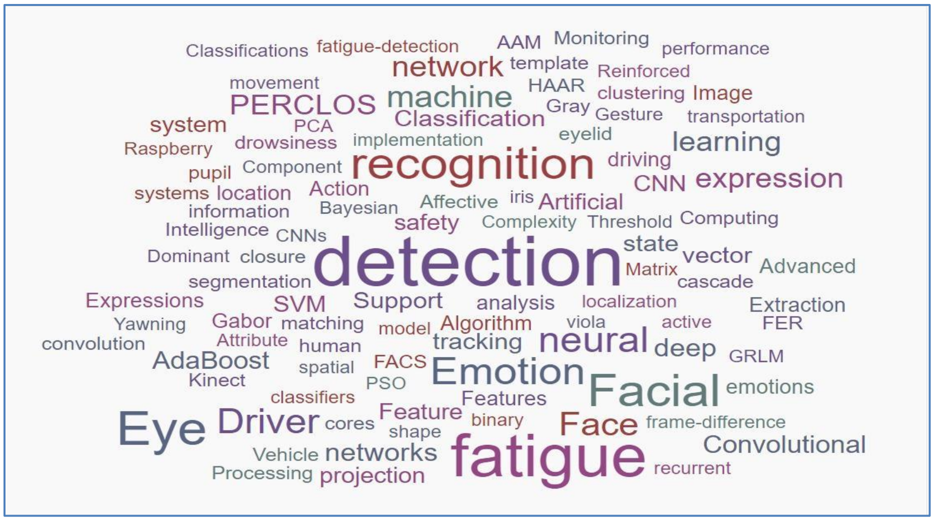


Figure 9. Word cloud illustrating the relevance of selected papers.

3.4 Data Analysis

A profiling exercise followed to identify the spread of research in this area in terms of keywords, the year of publication, and databases used to mine the papers. Analysis of the FER approaches in the selected papers were based on the feature extraction approaches, emotion detected, algorithms used, datasets used, application areas, and the result accuracy level. The next section presents the results of this analysis.

4. Review Results

4.1 Data Format

The solutions used for FER make use of data that exists in either Image or Video format. The majority of the studies (72% for Classic, 67% for Fatigue) made use of still images (Fa-deng & Min-xian, 2010; Gao & Wang, 2017; Huang et al., 2018; F. Li et al., 2020; H. Singh et al., 2011; Sravan et al., 2018; X. Sun et al., 2017) as illustrated in figure 10. Given that FER solutions should be able to work in real-life environments and provide feedback in real-time, studies that make use of videos would provide solutions that are more applicable in society. For example, if a driver's fatigue is detected from a video captured and processed while the driver is still driving, timely interventions can be realized.

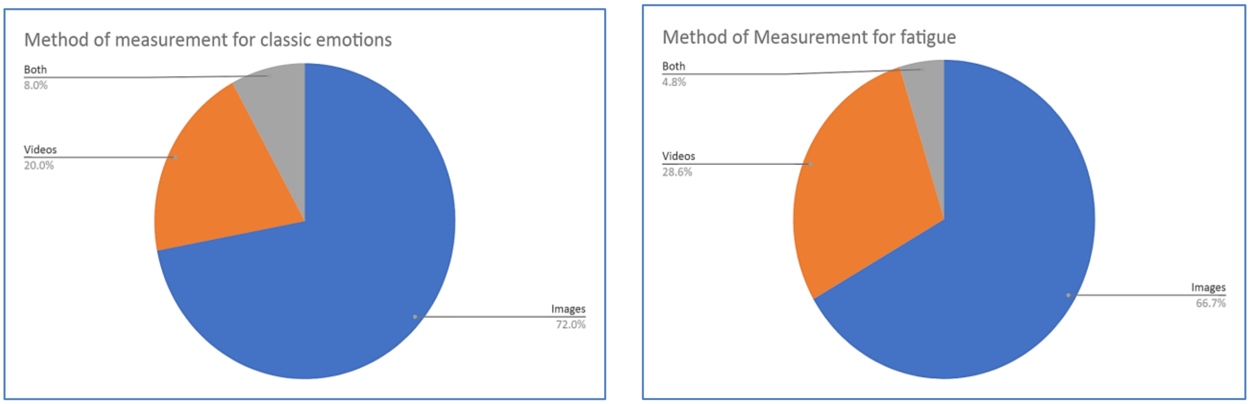
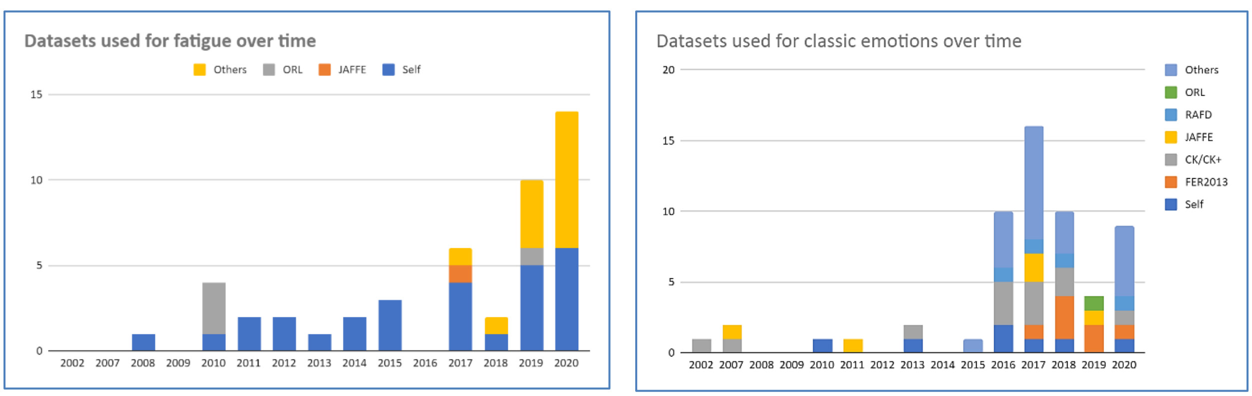


Figure 10. Input Data Format

4.2 Datasets Used

As mentioned in section 3.3, research in Fatigue Detection has increased over time, and consequently, the development of datasets to support the studies has increased. The analysis in Figure 11 shows an increase in the popularity of datasets created for specific studies (Abdulin & Komogortsev, 2015; Kurylyak et al., 2012; Le & Vea, 2016; F. Li et al., 2020; Z. Zhang et al., 2016) over time compared to publicly available open datasets (Gupta, 2018; Healy et al., 2018; Ithaya Rani & Muneeswaran, 2016; Loob et al., 2017; Rajesh & Naveenkumar, 2016; Sebe et al., 2007; L. Zhang et al., 2013) when monitoring fatigue compared to the classic emotions. This highlights the need for public open datasets applicable across multiple studies for monitoring other emotions such as fatigue. The list of datasets used for each study is provided in Table 5.



(a) Datasets for Fatigue Emotion (b) Datasets for Classic Emotions

Figure 11. Datasets used to detect different emotions over time.

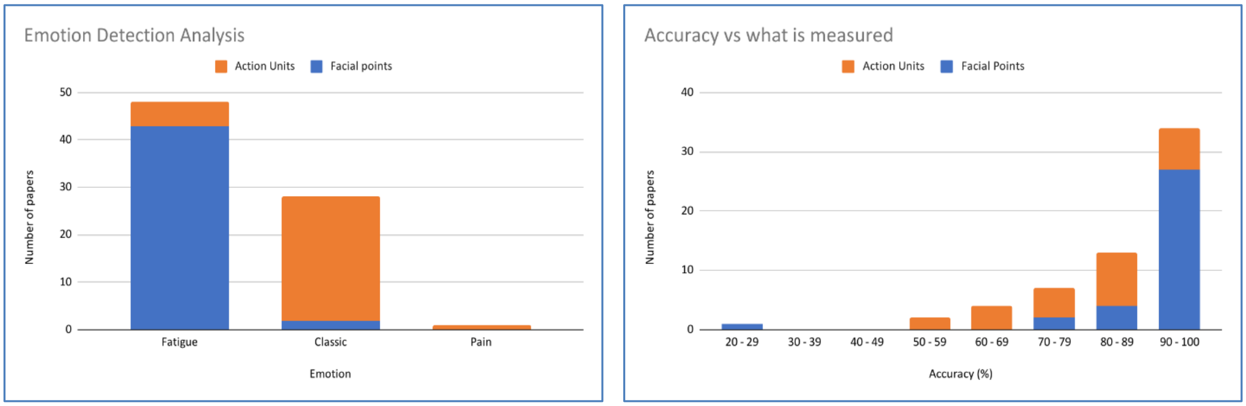
Table 5. Datasets used for different studies

Dataset	References
Self-made	(Abdulin & Komogortsev, 2015; Chang & Chen, 2014; Coetzer & Hancke, 2011; Cyganek & Gruszczyński, 2014; Fa-deng & Min-xian, 2010; Gao & Wang, 2017; Jie et al., 2010; Jing et al., 2020; M. I. Khan & Mansoor, 2008; Knapik & Cyganek, 2019; Kurylyak et al., 2012; F. Li et al., 2020; K. Li et al., 2019; L. Li et al., 2011; X. Li et al., 2015, 2015; Z. Li & Nianqiang, 2019; Maior et al., 2020; Nie et al., 2017; Punitha et al., 2014; Rakhmatulin & Duchowski, 2020; Rehman et al., 2018; Sharan et al., 2019; Song et al., 2020; Tang et al., 2010; F. Wang et al., 2020; Xie et al., 2012; F. Zhang et al., 2017)
ORL	(Fa-deng & Min-xian, 2010; Jie et al. 2010; Tang et al. 2010; Xing et al. 2019)
YanwnDD	(Huang & Wang, 2019; X.-W. Xu et al., 2020)
Caltech	(Z. Liu et al., 2020)
Cassia	(Kim & Lee, 2020)
Bath	(Kim & Lee, 2020)
Iris challenge Evaluation	(Kim & Lee, 2020)
IRF	(F. Zhang et al., 2017)
ZJU	(F. Zhang et al., 2017)
CEW human eye dataset	(S. Liu et al., 2019)
JAFFE	(Krestinskaya & James, 2017)
Drowsiness detection dataset	(Ed-doughmi & Idrissi, 2019)
WFLW	(Zhuang et al., 2020)
The 300-W Challenge	(Zhuang et al., 2020)
Helen	(Zhuang et al., 2020)
Closed eyes in the wild	(Huang et al., 2018)
Eye Blink database	(Huang & Wang, 2019)

This table shows popular datasets that are used. Datasets used only once such as WFLW (Zhuang et al., 2020), the 300-W Challenge (Zhuang et al., 2020), Helen, and Caltech faces (Z. Liu et al., 2020; Zhuang et al., 2020) are put in the others category. The results show that the type of emotion influences the choice of the dataset used. Datasets such as FER2013 and CK/CK+ are used for the classic facial emotions (Gan, 2018; Pranav et al., 2020; Ramdhani et al., 2018; S. Singh & Nasoz, 2020; X. Wang et al., 2018) while others such as JAFFE and ORL (Dagar et al., 2016; Deshmukh et al., 2017; Miyakoshi & Kato, 2011; Sebe et al., 2007) are used for both the classic emotions and Fatigue. The preference to use self-created datasets when monitoring fatigue (Abdulin & Komogortsev, 2015; Chang & Chen, 2014; Fa-deng & Min-xian, 2010; Gao & Wang, 2017; Kurylyak et al., 2012; F. Li et al., 2020) shows that existing datasets are not adequate. There is a need for open datasets in that area that facilitate results reproducibility. A similar scenario exists with the classic emotions where there is an apparent preference towards using a dataset in only one study (Deshmukh et al., 2017; Ithaya Rani & Muneeswaran, 2016; Mehendale, 2020; Rajesh & Naveenkumar, 2016; Yang et al., 2021) rather than using popular datasets such as FER2013 or CK/CK+. The results also show the possibility of detecting Fatigue without using datasets. For example, a popular approach (Chen, 2017; H. Singh et al., 2011; X. Sun et al., 2017) is the PERCLOS algorithm used to detect fatigue without the need for a dataset. PERCLOS is the percentage of eyelid closure over the pupil over time and reflects the proportion of time that the eyes are at least 80 percent closed. A driving simulator study established the PERCLOS drowsiness metric (Wierwille et al., 1994), currently considered as the most promising known real-time measures of alertness for drowsiness-detection systems in vehicles. This approach starts by detecting the eye using methods such as "Integro-differential operator" or using edge detection algorithms (Darshana et al., 2014).

4.3 Feature Extraction

Feature extraction refers to the mapping of image pixels into a feature space during the FER process. It reduces the initial set of raw image data to more manageable sizes for purposes of classification. Previous reviews (Liliana & Basaruddin, 2018) revealed Action Units (AU) and Facial Points (FP) analysis as two key methods used for Feature extraction of classic facial emotion. Action Units (AU) are numeric codes that describe the activity of facial muscles such as cheek raising, brow lowering, and nose wrinkling or upper lips movements. Action Units make use of Local Binary Patterns, Geometric Texture, Scale-Invariant Feature Transform, and Histogram of Oriented Gradients among other approaches. Facial Points (FP) analysis locates landmarks on a face such as eyes and mouth and uses them as control points (Liliana & Basaruddin, 2018). Facial Points make use of Restricted Boltzmann Machine, Wavelet motion, and edge detection approaches among others (Liliana & Basaruddin, 2018). The papers reviewed in this study revealed that Action Units are a popular feature extraction approach when analyzing the classic emotions or pain, exhibited in the entire face (Ghandi et al., 2010; Gilda et al., 2017; Guo et al., 2018; Gupta, 2018; Loob et al., 2017), while the eyes and mouth regions are preferred when analyzing emotions localized to specific areas in the face such as fatigue or drowsiness (Chen, 2017; Huang et al., 2018; Kurylyak et al., 2012; H. Singh et al., 2011; Sravan et al., 2018) as shown in figure 12(a). Further analysis revealed that the studies that used Facial points as a method of feature extraction yielded more accurate results compared to the studies that used action points for their experiments as shown in Figure 12 (b). These results are expected as facial points use a small region for feature extraction thus leading to higher accuracy rates. Table 6 presents a summary of the feature extraction approaches reported in the studies.



(a) Feature Extraction Approaches (b) Reported Emotion Detection accuracy

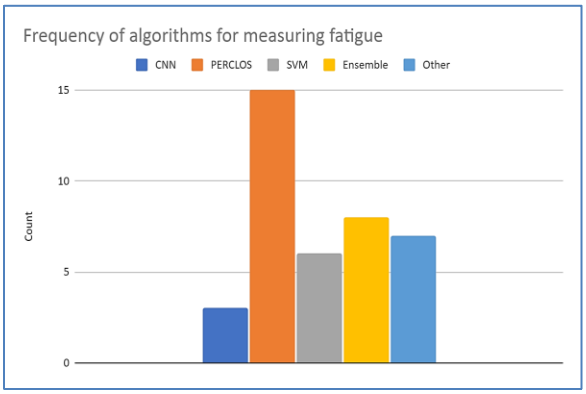
Figure 12. Feature Extraction Approaches and Emotion Detection Accuracy levels

Table 6. Feature Extraction Approaches used in different studies

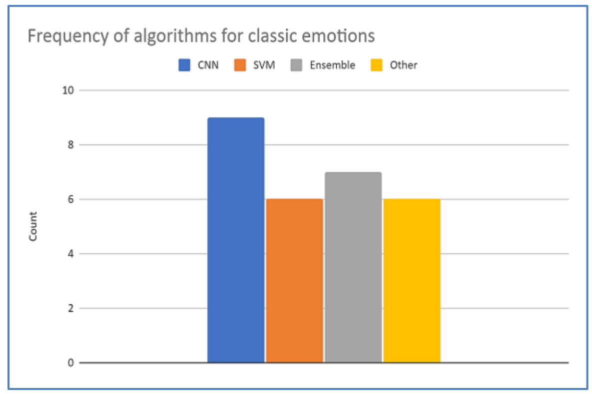
Emotion	References,
Facial Points	(Abdulin & Komogortsev, 2015; Bin et al., 2019; Chang & Chen, 2014; Chen, 2017; Coetzer & Hancke, 2011; Ed-doughmi & Idrissi, 2019; Fa-deng & Min-xian, 2010; Gao & Wang, 2017, p.; Huang et al., 2018; Huang & Wang, 2019; Jie et al., 2010; Kurylyak et al., 2012; F. Li et al., 2020; L. Li et al., 2011; X. Li et al., 2015; Z. Li & Nianqiang, 2019; S. Liu et al., 2019; Luo et al., 2013; Punitha et al., 2014; Rehman et al., 2018; Sharan et al., 2019; H. Singh et al., 2011; Sravan et al., 2018; X. Sun et al., 2017; Tang et al., 2010; Xie et al., 2012; Xing et al., 2019; X.-W. Xu et al., 2020; F. Zhang et al., 2017; Zhuang et al., 2020)
Action units	(Ramdhani et al., 2018; F. Wang et al., 2020)

4.4 Emotion Recognition

Several algorithms find applications in detecting facial expressions. Popular algorithms include CNN (Huang et al., 2018; Huang & Wang, 2019), SVM (Coetzer & Hancke, 2011; F. Li et al., 2020; Punitha et al., 2014; Rehman et al., 2018), and Ensemble approaches (Bin et al., 2019; Le & Vea, 2016; Sharan et al., 2019; Z. Zhang et al., 2016) for the classification of both the classic emotions and fatigue as illustrated in Figure 13. Some algorithms such as PERCLOS have found applications in detecting Fatigue only Figure 13 (a). Algorithms used in single studies for fatigue include K means clustering (Bin et al., 2019), I-VT (Abdulin & Komogortsev, 2015), Min-Max similarity Nearest Neighbor classifier (Krestinskaya & James, 2017), Deep belief network (F. Wang et al., 2020), Multiple kernel learning (F. Wang et al., 2020), and YOLOv3 (Rakhmatulin & Duchowski, 2020). Algorithms used in single studies for the classic emotions include Bagging (Le & Vea, 2016), J48 (Le & Vea, 2016), Random Committee (Le & Vea, 2016), and Random Tree (Z. Zhang et al., 2016). A Summary of the studies showing the emotion recognition algorithm for Fatigue Emotion is provided in table 7.



(a) Fatigue Emotion Recognition



(b) Classic Emotion Recognition

Figure 13. Emotion Recognition Algorithms

Table 7. Emotion Recognition Algorithms for Fatigue Emotion

Algorithm	References
CNN	(Bin et al., 2019; Ed-doughmi & Idrissi, 2019; Huang & Wang, 2019; Jie et al., 2010; Xing et al., 2019; F. Zhang et al., 2017)
PERCLOS	(Chen, 2017; Ed-doughmi & Idrissi, 2019; Gao & Wang, 2017; Jie et al., 2010; Kurylyak et al., 2012; L. Li et al., 2011; S. Liu et al., 2019; Z. Liu et al., 2020; Nie et al., 2017, p.; H. Singh et al., 2011; X. Sun et al., 2017; Xie et al., 2012; Xing et al., 2019; F. Zhang et al., 2017, 2017; Zhuang et al., 2020)
SVM	(Coetzer & Hancke, 2011; Kim & Lee, 2020; F. Li et al., 2020; K. Li et al., 2019; Punitha et al., 2014; Rehman et al., 2018; Song et al., 2020)
Ensemble	(Chang & Chen, 2014; Coetzer & Hancke, 2011; K. Li et al., 2019; Luo et al., 2013; Maior et al., 2020, 2020;

	Shahrabi Farahani et al., 2013; Sharan et al., 2019; F. Wang et al., 2020)
Others	(Abdulin & Komogortsev, 2015; Bin et al., 2019; Chang & Chen, 2014; Coetzer & Hancke, 2011; Cyganek & Gruszczyński, 2014; Jing et al., 2020; Krestinskaya & James, 2017; K. Li et al., 2019; Z. Li & Nianqiang, 2019; Luo et al., 2013; Rakhmatulin & Duchowski, 2020; Shahrabi Farahani et al., 2013; J. Xu et al., 2018; Zheng et al., 2016),

4.5 Implementation details.

Analysis of the implementation details provided by various studies revealed the extent of reporting of the solution design and results for purposes of reproducing the research. This analysis also renders confidence in the reliability of the studies examined, sheds light on the extent to which the solution was tested, and provides opportunities for comparison with future studies. Four implementation aspects were examined namely algorithm expressions, solution architecture, solution design, and results. Based on these criteria, circular symbols with each quadrant representing one of the criteria visualized the findings as shown in Table 8. A full circle indicates that all categories were present, three-quarters circles represent three categories, semi-circles represent two categories, a quarter represents only one category, and an empty circle represents none. The results, illustrated in Table 8, reveal that only a few studies provided comprehensive implementation details (Bin et al., 2019; Jing et al., 2020; Knapik & Cyganek, 2019; Rakhmatulin & Duchowski, 2020; Song et al., 2020; M. Wang et al., 2017; L. Zhang et al., 2013; Zheng et al., 2016). Majority of the studies provided partial implementation details (Gupta, 2018; Healy et al., 2018; Loob et al., 2017; Miyakoshi & Kato, 2011; Park et al., 2015), with a few providing no details at all (Ivanova & Borzunov, 2020; Jing et al., 2020; Rehman et al., 2018). This observation is similar to the different emotions examined in this study.

Table 8. Implementation details used in different studies

Emotion	Reference\study	Implementation detail Reported
Fatigue	(Jing et al., 2020)	○
	(Bin et al., 2019; Coetzer & Hancke, 2011; Fa-deng & Min-xian, 2010; F. Li et al., 2020; L. Li et al., 2011; Z. Li & Nianqiang, 2019; Rakhmatulin & Duchowski, 2020; Shahrabi Farahani et al., 2013; H. Singh et al., 2011; Xie et al., 2012)	◔
	(A. B. Ashraf et al., 2009; Chang & Chen, 2014; Chen, 2017; Huang et al., 2018; Iatsun et al., 2015; K. Li et al., 2019; X. Li et al., 2015; S. Liu et al., 2019; Luo et al., 2013; Punitha et al., 2014; Sharan et al., 2019; Sravan et al., 2018; X.-W. Xu et al., 2020; Zhuang et al., 2020)	◒
	(Abdulin & Komogortsev, 2015; Cyganek & Gruszczyński, 2014; Ed-doughmi & Idrissi, 2019; Huang & Wang, 2019; Jie et al., 2010; M. I. Khan & Mansoor, 2008; Kim & Lee, 2020; Krestinskaya & James, 2017; Kurylyak et al., 2012; Z. Liu et al., 2020; Maior et al., 2020; Nie et al., 2017, p.; Punitha et al., 2014; X. Sun et al., 2017; Tang et al., 2010; Y. Wang et al., 2019; Xing et al., 2019; J. Xu et al., 2018; F. Zhang et al., 2017)	◕
	(Knapik & Cyganek, 2019; Song et al., 2020; F. Wang et al., 2020; M. Wang et al., 2017; Zheng et al., 2016)	●
Classic Emotions	(Deshmukh et al., 2017; Ivanova & Borzunov, 2020; Rehman et al., 2018)	○
	(Ivanova & Borzunov, 2020; Lim et al., 2020; Rajesh & Naveenkumar, 2016; Turabzadeh et al., 2017)	◔
	(Dagar et al., 2016; Gupta, 2018; Healy et al., 2018; Ithaya Rani & Muneeswaran, 2016; Loob et al., 2017; Miyakoshi & Kato, 2011; Park et al., 2015; Sebe et al., 2007; S. Singh & Nasoz, 2020; J.-M. Sun et al., 2008; Xiaoxi et al., 2017; Z. Zhang et al., 2016)	◒
	(Gan, 2018; Ghandi et al., 2010; Gilda et al., 2017; Guo et al., 2018; Hickson et al., 2019; Le & Vea, 2016; Mohammadpour et al., 2017; Pranav et al., 2020; Ramdhani et al., 2018; X. Wang et al., 2018; F. Zhang et al., 2016)	◕
	(Mehendale, 2020; Yang et al., 2021; L. Zhang et al., 2013)	●

5. Conclusion

This review set out to investigate the current state of research on the use of Machine learning for facial expression recognition. The review identified and analyzed eighty-three papers. The papers highlighted the gaps in existing research, noting that facial expression recognition algorithms and datasets depend on the type of emotion. There are, however, some limitations of the review findings presented in this paper. At present, Facial Expression Recognition studies have focused on only two types of emotions, that is classic emotions or driver fatigue. Additionally, most of the studies reviewed provided limited implementation details thereby limiting the findings from the comparative analysis. Future FER reviews should therefore incorporate studies with more emotions such as digitization, eyestrain, or health ailments manifested through facial expressions. Our future work will focus on developing a FER solution that detects different emotions outside of the classic and Fatigue emotions, to explore how FER techniques vary depending on the emotion in question.

References

Abdulin, E., & Komogortsev, O. (2015). User Eye Fatigue Detection via Eye Movement Behavior. *Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems*, 1265–1270. https://doi.org/10.1145/2702613.2732812

Adeshina, A. M., Lau, S.-H., & Loo, C.-K. (2009). Real-time facial expression recognitions: A review. *2009 Innovative Technologies in Intelligent Systems and Industrial Applications*, 375–378. https://doi.org/10.1109/CITISIA.2009.5224179

Ashraf, A. B., Lucey, S., Cohn, J. F., Chen, T., Ambadar, Z., Prkachin, K. M., & Solomon, P. E. (2009). The painful face – Pain expression recognition using active appearance models. *Image and Vision Computing*, *27*(12), 1788–1796. https://doi.org/10.1016/j.imavis.2009.05.007

Ashraf, H., Sodergren, M. H., Merali, N., Mylonas, G., Singh, H., & Darzi, A. (2018). Eye-tracking technology in medical education: A systematic review. *Medical Teacher*, *40*(1), 62–69. https://doi.org/10.1080/0142159X.2017.1391373

Balasubramanian, B., Diwan, P., Nadar, R., & Bhatia, A. (2019). Analysis of Facial Emotion Recognition. *2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI)*, 945–949. https://doi.org/10.1109/ICOEI.2019.8862731

Baskar, A., & Gireesh Kumar, T. (2018). Facial Expression Classification Using Machine Learning Approach: A Review. In S. C. Satapathy, V. Bhateja, K. S. Raju, & B. Janakiramaiah (Eds.), *Data Engineering and Intelligent Computing* (pp. 337–345). Springer. https://doi.org/10.1007/978-981-10-3223-3_32

Bhattacharya, S., & Gupta, M. (2019). A Survey on: Facial Emotion Recognition Invariant to Pose, Illumination and Age. *2019 Second International Conference on Advanced Computational and Communication Paradigms (ICACCP)*, 1–6. https://doi.org/10.1109/ICACCP.2019.8883015

Bin, F., Shuo, X., & Xiaofeng, F. (2019). A Fatigue Driving Detection Method Based on Multi Facial Features Fusion. *2019 11th International Conference on Measuring Technology and Mechatronics Automation (ICMTMA)*, 225–229. https://doi.org/10.1109/ICMTMA.2019.00057

Canedo, D., & Neves, A. J. R. (2019). Facial Expression Recognition Using Computer Vision: A Systematic Review. *Applied Sciences*, *9*(21), 4678. https://doi.org/10.3390/app9214678

Chang, T.-H., & Chen, Y.-R. (2014). Driver fatigue surveillance via eye detection. *17th International IEEE Conference on Intelligent Transportation Systems (ITSC)*, 366–371. https://doi.org/10.1109/ITSC.2014.6957718

Chen, P. (2017). Research on driver fatigue detection strategy based on human eye state. *2017 Chinese Automation Congress (CAC)*, 619–623. https://doi.org/10.1109/CAC.2017.8242842

Chengeta, K. (2019). A Review of Local Feature Algorithms and Deep Learning Approaches in Facial Expression Recognition with Tensorflow and Keras. In J. A. Carrasco-Ochoa, J. F. Martínez-Trinidad, J. A. Olvera-López, & J. Salas (Eds.), *Pattern Recognition* (pp. 127–138). Springer International Publishing. https://doi.org/10.1007/978-3-030-21077-9_12

Coetzer, R. C., & Hancke, G. P. (2011). Eye detection for a real-time vehicle driver fatigue monitoring system. *2011 IEEE Intelligent Vehicles Symposium (IV)*, 66–71. https://doi.org/10.1109/IVS.2011.5940406

Cyganek, B., & Gruszczyński, S. (2014). Hybrid computer vision system for drivers' eye recognition and fatigue monitoring. *Neurocomputing*, *126*, 78–94. https://doi.org/10.1016/j.neucom.2013.01.048

Dagar, D., Hudait, A., Tripathy, H. K., & Das, M. N. (2016). Automatic emotion detection model from facial expression. *2016 International Conference on Advanced Communication Control and Computing Technologies (ICACCCT)*, 77–85. https://doi.org/10.1109/ICACCCT.2016.7831605

Darshana, S., Fernando, D., Jayawardena, S., Wickramanayake, S., & DeSilva, C. (2014). Efficient PERCLOS and Gaze Measurement Methodologies to Estimate Driver Attention in Real Time. *Modelling and Simulation 2014 5th International Conference on Intelligent Systems*, 289–294. https://doi.org/10.1109/ISMS.2014.56

Deshmukh, R. S., Jagtap, V., & Paygude, S. (2017). Facial emotion recognition system through machine learning approach. *2017 International Conference on Intelligent Computing and Control Systems (ICICCS)*, 272–277. https://doi.org/10.1109/ICCONS.2017.8250725

Dzedzickis, A., Kaklauskas, A., & Bucinskas, V. (2020). Human Emotion Recognition: Review of Sensors and Methods. *Sensors*, *20*(3), 592. https://doi.org/10.3390/s20030592

Ed-doughmi, Y., & Idrissi, N. (2019). Driver Fatigue Detection using Recurrent Neural Networks. *Proceedings of the 2nd International Conference on Networking, Information Systems & Security*, 1–6. https://doi.org/10.1145/3320326.3320376

Edwards, J., Jackson, H. J., & Pattison, P. E. (2002). Emotion recognition via facial expression and affective prosody in schizophrenia: A methodological review. *Clinical Psychology Review*, *22*(6), 789–832. https://doi.org/10.1016/S0272-7358(02)00130-7

Egger, M., Ley, M., & Hanke, S. (2019). Emotion Recognition from Physiological Signal Analysis: A Review. *Electronic Notes in Theoretical Computer Science*, *343*, 35–55. https://doi.org/10.1016/j.entcs.2019.04.009

Fa-deng, G., & Min-xian, H. (2010). Study on the detection of locomotive driver fatigue based on image. *2010 2nd International Conference on Computer Engineering and Technology*, *7*, V7-612-V7-615. https://doi.org/10.1109/ICCET.2010.5485638

Fathima, A., & Vaidehi, K. (2020). Review on Facial Expression Recognition System Using Machine Learning Techniques. In S. C. Satapathy, K. S. Raju, K. Shyamala, D. R. Krishna, & M. N. Favorskaya (Eds.), *Advances in Decision Sciences, Image Processing, Security and Computer Vision* (pp. 608–618). Springer International Publishing. https://doi.org/10.1007/978-3-030-24318-0_70

Gan, Y. (2018). Facial Expression Recognition Using Convolutional Neural Network. *Proceedings of the 2nd International Conference on Vision, Image and Signal Processing*, 1–5. https://doi.org/10.1145/3271553.3271584

Gantayat, S. S., & Lenka, S. (2021). Study of Algorithms and Methods on Emotion Detection from Facial Expressions: A Review from Past Research. In S. C. Satapathy, V. Bhateja, M. Ramakrishna Murty, N. Gia Nhu, & Jayasri Kotti (Eds.), *Communication Software and Networks* (pp. 231–244). Springer. https://doi.org/10.1007/978-981-15-5397-4_24

Gao, Y., & Wang, C. (2017). Fatigue state detection from multi-feature of eyes. *2017 4th International Conference on Systems and Informatics (ICSAI)*, 177–181. https://doi.org/10.1109/ICSAI.2017.8248285

Ghandi, B. M., Nagarajan, R., & Desa, H. (2010). Real-time system for facial emotion detection using GPSO algorithm. *2010 IEEE Symposium on Industrial Electronics and Applications (ISIEA)*, 40–45. https://doi.org/10.1109/ISIEA.2010.5679500

Gilda, S., Zafar, H., Soni, C., & Waghurdekar, K. (2017). Smart music player integrating facial emotion recognition and music mood recommendation. *2017 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*, 154–158. https://doi.org/10.1109/WiSPNET.2017.8299738

Guo, J., Lei, Z., Wan, J., Avots, E., Hajarolasvadi, N., Knyazev, B., Kuharenko, A., Jacques Junior, J. C. S., Baró, X., Demirel, H., Escalera, S., Allik, J., & Anbarjafari, G. (2018). Dominant and Complementary Emotion Recognition From Still Images of Faces. *IEEE Access*, *6*, 26391–26403. https://doi.org/10.1109/ACCESS.2018.2831927

Gupta, S. (2018). Facial emotion recognition in real-time and static images. *2018 2nd International Conference on Inventive Systems and Control (ICISC)*, 553–560. https://doi.org/10.1109/ICISC.2018.8398861

Harms, M. B., Martin, A., & Wallace, G. L. (2010). Facial Emotion Recognition in Autism Spectrum Disorders: A Review of Behavioral and Neuroimaging Studies. *Neuropsychology Review*, *20*(3), 290–322. https://doi.org/10.1007/s11065-010-9138-6

Healy, M., Donovan, R., Walsh, P., & Zheng, H. (2018). A Machine Learning Emotion Detection Platform to Support Affective Well Being. *2018 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, 2694–2700. https://doi.org/10.1109/BIBM.2018.8621562

Hickson, S., Dufour, N., Sud, A., Kwatra, V., & Essa, I. (2019). Eyemotion: Classifying Facial Expressions in VR Using Eye-Tracking Cameras. *2019 IEEE Winter Conference on Applications of Computer Vision (WACV)*, 1626–1635. https://doi.org/10.1109/WACV.2019.00178

Huang, R., & Wang, Y. (2019). Information interaction based two-stream neural networks for fatigue detection. *Proceedings of the 2nd International Conference on Artificial Intelligence and Pattern Recognition*, 1–5. https://doi.org/10.1145/3357254.3357257

Huang, R., Wang, Y., & Guo, L. (2018). P-FDCN Based Eye State Analysis for Fatigue Detection. *2018 IEEE 18th International Conference on Communication Technology (ICCT)*, 1174–1178. https://doi.org/10.1109/ICCT.2018.8599947

Iatsun, I., Larabi, M.-C., & Fernandez-Maloigne, C. (2015). Investigation and modeling of visual fatigue caused by S3D content using eye-tracking. *Displays, 39*, 11–25. https://doi.org/10.1016/j.displa.2015.07.001

Ithaya Rani, P., & Muneeswaran, K. (2016). Facial Emotion Recognition Based on Eye and Mouth Regions. *International Journal of Pattern Recognition and Artificial Intelligence*, *30*(07), 1655020. https://doi.org/10.1142/S021800141655020X

Ivanova, E., & Borzunov, G. (2020). Optimization of machine learning algorithm of emotion recognition in terms of human facial expressions. *Procedia Computer Science*, *169*, 244–248. https://doi.org/10.1016/j.procs.2020.02.143

Jie, T., Zuhua, F., Shifeng, H., & Ying, S. (2010). Research of driver fatigue detection system based on ADSP-BF548. *2010 International Conference on Mechanic Automation and Control Engineering*, 3380–3383. https://doi.org/10.1109/MACE.2010.5536444

Jing, D., Liu, D., Zhang, S., & Guo, Z. (2020). Fatigue driving detection method based on EEG analysis in low-voltage and hypoxia plateau environment. *International Journal of Transportation Science and Technology*, *9*(4), 366–376. https://doi.org/10.1016/j.ijtst.2020.03.008

Jonathan, Lim, A. P., Paoline, Kusuma, G. P., & Zahra, A. (2018). Facial Emotion Recognition Using Computer Vision. *2018 Indonesian Association for Pattern Recognition International Conference (INAPR)*, 46–50. https://doi.org/10.1109/INAPR.2018.8626999

Kartali, A., Roglić, M., Barjaktarović, M., Đurić-Jovičić, M., & Janković, M. M. (2018). Real-time Algorithms for Facial Emotion Recognition: A Comparison of Different Approaches. *2018 14th Symposium on Neural Networks and Applications (NEUREL)*, 1–4. https://doi.org/10.1109/NEUREL.2018.8587011

Khan, M. I., & Mansoor, A. B. (2008). Real Time Eyes Tracking and Classification for Driver Fatigue Detection. In A. Campilho & M. Kamel (Eds.), *Image Analysis and Recognition* (pp. 729–738). Springer. https://doi.org/10.1007/978-3-540-69812-8_72

Khan, M. Q., & Lee, S. (2019). Gaze and Eye Tracking: Techniques and Applications in ADAS. *Sensors*, *19*(24), 5540. https://doi.org/10.3390/s19245540

Kim, T., & Lee, E. C. (2020). Experimental Verification of Objective Visual Fatigue Measurement Based on Accurate Pupil Detection of Infrared Eye Image and Multi-Feature Analysis. *Sensors*, *20*(17), 4814. https://doi.org/10.3390/s20174814

Klaib, A. F., Alsrehin, N. O., Melhem, W. Y., Bashtawi, H. O., & Magableh, A. A. (2021). Eye tracking algorithms, techniques, tools, and applications with an emphasis on machine learning and Internet of Things technologies. *Expert Systems with Applications*, *166*, 114037. https://doi.org/10.1016/j.eswa.2020.114037

Knapik, M., & Cyganek, B. (2019). Driver's fatigue recognition based on yawn detection in thermal images. *Neurocomputing*, *338*, 274–292. https://doi.org/10.1016/j.neucom.2019.02.014

Krestinskaya, O., & James, A. P. (2017). Facial emotion recognition using min-max similarity classifier. *2017 International Conference on Advances in Computing, Communications and Informatics (ICACCI)*, 752–758. https://doi.org/10.1109/ICACCI.2017.8125932

Kurylyak, Y., Lamonaca, F., & Mirabelli, G. (2012). Detection of the eye blinks for human's fatigue monitoring. *2012 IEEE International Symposium on Medical Measurements and Applications Proceedings*, 1–4. https://doi.org/10.1109/MeMeA.2012.6226666

Le, H. T., & Vea, L. A. (2016). A Customer Emotion Recognition through Facial Expression using Kinect Sensors v1 and v2: A Comparative Analysis. *Proceedings of the 10th International Conference on Ubiquitous Information Management and Communication*, 1–7. https://doi.org/10.1145/2857546.2857628

Li, F., Chen, C.-H., Xu, G., & Khoo, L.-P. (2020). Hierarchical Eye-Tracking Data Analytics for Human Fatigue Detection at a Traffic Control Center. *IEEE Transactions on Human-Machine Systems*, *50*(5), 465–474. https://doi.org/10.1109/THMS.2020.3016088

Li, K., Wang, S., Du, C., Huang, Y., Feng, X., & Zhou, F. (2019). Accurate Fatigue Detection Based on Multiple Facial Morphological Features. *Journal of Sensors*, *2019*, e7934516. https://doi.org/10.1155/2019/7934516

Li, L., Xie, M., & Dong, H. (2011). A method of driving fatigue detection based on eye location. *2011 IEEE 3rd International Conference on Communication Software and Networks*, 480–484. https://doi.org/10.1109/ICCSN.2011.6013949

Li, S., & Deng, W. (2020). Deep Facial Expression Recognition: A Survey. *IEEE Transactions on Affective Computing*, 1–1. https://doi.org/10.1109/TAFFC.2020.2981446

Li, X., Wu, Q., Kou, Y., Hou, L., & Xie, H. (2015). Driver's Eyes State Detection Based on Adaboost Algorithm and Image Complexity. *2015 Sixth International Conference on Intelligent Systems Design and Engineering Applications (ISDEA)*, 349–352. https://doi.org/10.1109/ISDEA.2015.93

Li, Z., & Nianqiang, L. (2019). Fatigue Driving Detection System Based on Face Feature. *2019 IEEE 2nd International Conference on Electronics Technology (ICET)*, 525–529. https://doi.org/10.1109/ELTECH.2019.8839479

Liliana, D. Y., & Basaruddin, T. (2018). Review of Automatic Emotion Recognition Through Facial Expression Analysis. *2018 International Conference on Electrical Engineering and Computer Science (ICECOS)*, 231–236. https://doi.org/10.1109/ICECOS.2018.8605222

Lim, J. Z., Mountstephens, J., & Teo, J. (2020). Emotion Recognition Using Eye-Tracking: Taxonomy, Review and Current Challenges. *Sensors*, *20*(8), 2384. https://doi.org/10.3390/s20082384

Lin, L., Huang, C., Ni, X., Wang, J., Zhang, H., Li, X., & Qian, Z. (2015). Driver fatigue detection based on eye state. *Technology and Health Care*, *23*(s2), S453–S463. https://doi.org/10.3233/THC-150982

Liu, S., Yu, L., & Hou, M. (2019). An efficient method for driver fatigue state detection based on deep learning. *2019 2nd International Conference on Safety Produce Informatization (IICSPI)*, 172–176. https://doi.org/10.1109/IICSPI48186.2019.9095909

Liu, Z., Peng, Y., & Hu, W. (2020). Driver fatigue detection based on deeply-learned facial expression representation. *Journal of Visual Communication and Image Representation*, *71*, 102723. https://doi.org/10.1016/j.jvcir.2019.102723

Loob, C., Rasti, P., Lüsi, I., Jacques, J. C. S., Baró, X., Escalera, S., Sapinski, T., Kaminska, D., & Anbarjafari, G. (2017). Dominant and Complementary Multi-Emotional Facial Expression Recognition Using C-Support Vector Classification. *2017 12th IEEE*

International Conference on Automatic Face Gesture Recognition (FG 2017), 833–838. https://doi.org/10.1109/FG.2017.106

Luo, X., Hu, R., & Fan, T. (2013). The driver fatigue monitoring system based on face recognition technology. *2013 Fourth International Conference on Intelligent Control and Information Processing (ICICIP)*, 384–388. https://doi.org/10.1109/ICICIP.2013.6568102

Maior, C. B. S., Moura, M. J. das C., Santana, J. M. M., & Lins, I. D. (2020). Real-time classification for autonomous drowsiness detection using eye aspect ratio. *Expert Systems with Applications*, *158*, 113505. https://doi.org/10.1016/j.eswa.2020.113505

McKinley, R. A., McIntire, L. K., Schmidt, R., Repperger, D. W., & Caldwell, J. A. (2011). Evaluation of Eye Metrics as a Detector of Fatigue. *Human Factors*, *53*(4), 403–414. https://doi.org/10.1177/0018720811411297

Mehendale, N. (2020). Facial emotion recognition using convolutional neural networks (FERC). *SN Applied Sciences*, *2*(3), 446. https://doi.org/10.1007/s42452-020-2234-1

Mellouk, W., & Handouzi, W. (2020). Facial emotion recognition using deep learning: Review and insights. *Procedia Computer Science*, *175*, 689–694. https://doi.org/10.1016/j.procs.2020.07.101

Michel, P., & El Kaliouby, R. (2003). Real time facial expression recognition in video using support vector machines. *Proceedings of the 5th International Conference on Multimodal Interfaces*, 258–264. https://doi.org/10.1145/958432.958479

Miyakoshi, Y., & Kato, S. (2011). Facial emotion detection considering partial occlusion of face using Bayesian network. *2011 IEEE Symposium on Computers Informatics*, 96–101. https://doi.org/10.1109/ISCI.2011.5958891

Mohammadpour, M., Khaliliardali, H., Hashemi, S. Mohammad. R., & AlyanNezhadi, Mohammad. M. (2017). Facial emotion recognition using deep convolutional networks. *2017 IEEE 4th International Conference on Knowledge-Based Engineering and Innovation (KBEI)*, 0017–0021. https://doi.org/10.1109/KBEI.2017.8324974

Nie, B., Huang, X., Chen, Y., Li, A., Zhang, R., & Huang, J. (2017). Experimental study on visual detection for fatigue of fixed-position staff. *Applied Ergonomics*, *65*, 1–11. https://doi.org/10.1016/j.apergo.2017.05.010

Park, S. Y., Lee, S. H., & Ro, Y. M. (2015). Subtle Facial Expression Recognition Using Adaptive Magnification of Discriminative Facial Motion. *Proceedings of the 23rd ACM International Conference on Multimedia*, 911–914. https://doi.org/10.1145/2733373.2806362

Pranav, E., Kamal, S., Satheesh Chandran, C., & Supriya, M. H. (2020). Facial Emotion Recognition Using Deep Convolutional Neural Network. *2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS)*, 317–320. https://doi.org/10.1109/ICACCS48705.2020.9074302

Punitha, A., Geetha, M. K., & Sivaprakash, A. (2014). Driver fatigue monitoring system based on eye state analysis. *2014 International Conference on Circuits, Power and Computing Technologies [ICCPCT-2014]*, 1405–1408. https://doi.org/10.1109/ICCPCT.2014.7055020

Rajesh, K. M., & Naveenkumar, M. (2016). A robust method for face recognition and face emotion detection system using support vector machines. *2016 International Conference on*

Electrical, Electronics, Communication, Computer and Optimization Techniques (ICEECCOT), 1–5. https://doi.org/10.1109/ICEECCOT.2016.7955175

Rakhmatulin, I., & Duchowski, A. T. (2020). Deep Neural Networks for Low-Cost Eye Tracking. *Procedia Computer Science*, *176*, 685–694. https://doi.org/10.1016/j.procs.2020.09.041

Ramdhani, B., Djamal, E. C., & Ilyas, R. (2018). Convolutional Neural Networks Models for Facial Expression Recognition. *2018 International Symposium on Advanced Intelligent Informatics (SAIN)*, 96–101. https://doi.org/10.1109/SAIN.2018.8673352

Ray, C., Tripathy, H. K., & Mishra, S. (2019). A Review on Facial Expression Based Behavioral Analysis Using Computational Technique for Autistic Disorder Patients. In M. Singh, P. K. Gupta, V. Tyagi, J. Flusser, T. Ören, & R. Kashyap (Eds.), *Advances in Computing and Data Sciences* (pp. 450–464). Springer. https://doi.org/10.1007/978-981-13-9942-8_43

Rehman, H. U., Naeem, M., Khan, M., Sikander, G., & Anwar, S. (2018). Eye Tracking based Real- Time Non-Interfering Driver Fatigue Detection System. *2018 10th International Conference on Electronics, Computers and Artificial Intelligence (ECAI)*, 1–5. https://doi.org/10.1109/ECAI.2018.8678951

Sabu, E., & Mathai, P. P. (2015). An extensive review of facial expression recognition using salient facial patches. *2015 International Conference on Applied and Theoretical Computing and Communication Technology (ICATccT)*, 847–581. https://doi.org/10.1109/ICATCCT.2015.7457001

Samadiani, N., Huang, G., Cai, B., Luo, W., Chi, C.-H., Xiang, Y., & He, J. (2019). A Review on Automatic Facial Expression Recognition Systems Assisted by Multimodal Sensor Data. *Sensors*, *19*(8), 1863. https://doi.org/10.3390/s19081863

Sebe, N., Lew, M. S., Sun, Y., Cohen, I., Gevers, T., & Huang, T. S. (2007). Authentic facial expression analysis. *Image and Vision Computing*, *25*(12), 1856–1863. https://doi.org/10.1016/j.imavis.2005.12.021

Shahrabi Farahani, F., Sheikhan, M., & Farrokhi, A. (2013). A fuzzy approach for facial emotion recognition. *2013 13th Iranian Conference on Fuzzy Systems (IFSC)*, 1–4. https://doi.org/10.1109/IFSC.2013.6675597

Sharan, S. S., Viji, R., Pradeep, R., & Sajith, V. (2019). Driver Fatigue Detection Based On Eye State Recognition Using Convolutional Neural Network. *2019 International Conference on Communication and Electronics Systems (ICCES)*, 2057–2063. https://doi.org/10.1109/ICCES45898.2019.9002215

Shu, L., Xie, J., Yang, M., Li, Z., Li, Z., Liao, D., Xu, X., & Yang, X. (2018). A Review of Emotion Recognition Using Physiological Signals. *Sensors*, *18*(7), 2074. https://doi.org/10.3390/s18072074

Singh, H., Bhatia, J. S., & Kaur, J. (2011). Eye tracking based driver fatigue monitoring and warning system. *India International Conference on Power Electronics 2010 (IICPE2010)*, 1–6. https://doi.org/10.1109/IICPE.2011.5728062

Singh, S., & Nasoz, F. (2020). Facial Expression Recognition with Convolutional Neural Networks. *2020 10th Annual Computing and Communication Workshop and Conference (CCWC)*, 0324–0328. https://doi.org/10.1109/CCWC47524.2020.9031283

Song, M., Li, L., Guo, J., Liu, T., Li, S., Wang, Y., Qurat ul ain, & Wang, J. (2020). A new method for muscular visual fatigue detection using electrooculogram. *Biomedical Signal Processing and Control*, *58*, 101865. https://doi.org/10.1016/j.bspc.2020.101865

Sravan, Ch., Onesim, K. J., Bhavana, V. S. S., Arthi, R., & Srinadh, G. (2018). Eye Fatigue Detection System. *2018 International Conference on System Modeling Advancement in Research Trends (SMART)*, 245–247. https://doi.org/10.1109/SYSMART.2018.8746956

Sun, J.-M., Pei, X.-S., & Zhou, S.-S. (2008). Facial emotion recognition in modern distant education system using SVM. *2008 International Conference on Machine Learning and Cybernetics*, *6*, 3545–3548. https://doi.org/10.1109/ICMLC.2008.4621018

Sun, X., Lan, C., & Mao, X. (2017). Eye locating arithmetic in fatigue detection based on image processing. *2017 10th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI)*, 1–5. https://doi.org/10.1109/CISP-BMEI.2017.8301954

Tang, J., Fang, Z., Hu, S., & Sun, Y. (2010). Driver fatigue detection algorithm based on eye features. *2010 Seventh International Conference on Fuzzy Systems and Knowledge Discovery*, *5*, 2308–2311. https://doi.org/10.1109/FSKD.2010.5569306

Turabzadeh, S., Meng, H., Swash, R. M., Pleva, M., & Juhar, J. (2017). Real-time emotional state detection from facial expression on embedded devices. *2017 Seventh International Conference on Innovative Computing Technology (INTECH)*, 46–51. https://doi.org/10.1109/INTECH.2017.8102423

Wagh, K. P., & Vasanth, K. (2019). Electroencephalograph (EEG) Based Emotion Recognition System: A Review. In H. S. Saini, R. K. Singh, V. M. Patel, K. Santhi, & S. V. Ranganayakulu (Eds.), *Innovations in Electronics and Communication Engineering* (pp. 37–59). Springer. https://doi.org/10.1007/978-981-10-8204-7_5

Wang, F., Wu, S., Zhang, W., Xu, Z., Zhang, Y., & Chu, H. (2020). Multiple nonlinear features fusion based driving fatigue detection. *Biomedical Signal Processing and Control*, *62*, 102075. https://doi.org/10.1016/j.bspc.2020.102075

Wang, M., Guo, L., & Chen, W.-Y. (2017). Blink detection using Adaboost and contour circle for fatigue recognition. *Computers & Electrical Engineering*, *58*, 502–512. https://doi.org/10.1016/j.compeleceng.2016.09.008

Wang, X., Huang, J., Zhu, J., Yang, M., & Yang, F. (2018). Facial expression recognition with deep learning. *Proceedings of the 10th International Conference on Internet Multimedia Computing and Service*, 1–4. https://doi.org/10.1145/3240876.3240908

Wang, Y., Zhai, G., Chen, S., Min, X., Gao, Z., & Song, X. (2019). Assessment of eye fatigue caused by head-mounted displays using eye-tracking. *BioMedical Engineering OnLine*, *18*(1), 111. https://doi.org/10.1186/s12938-019-0731-5

Wierwille, W. W., Wreggit, S. S., Kirn, C. L., Ellsworth, L. A., & Fairbanks, R. J. (1994). *RESEARCH ON VEHICLE-BASED DRIVER STATUS/PERFORMANCE MONITORING; DEVELOPMENT, VALIDATION, AND REFINEMENT OF ALGORITHMS FOR DETECTION OF DRIVER DROWSINESS. FINAL REPORT* (HS-808 247). Article HS-808 247. https://trid.trb.org/view/448128

Xiaoxi, M., Weisi, L., Dongyan, H., Minghui, D., & Li, H. (2017). Facial emotion recognition. *2017 IEEE 2nd International Conference on Signal and Image Processing (ICSIP)*, 77–81. https://doi.org/10.1109/SIPROCESS.2017.8124509

Xie, J.-F., Xie, M., & Zhu, W. (2012). Driver fatigue detection based on head gesture and PERCLOS. *2012 International Conference on Wavelet Active Media Technology and Information Processing (ICWAMTIP)*, 128–131. https://doi.org/10.1109/ICWAMTIP.2012.6413456

Xing, J., Fang, G., Zhong, J., & Li, J. (2019). Application of Face Recognition Based on CNN in Fatigue Driving Detection. *Proceedings of the 2019 International Conference on Artificial Intelligence and Advanced Manufacturing*, 1–5. https://doi.org/10.1145/3358331.3358387

Xu, J., Min, J., & Hu, J. (2018). Real-time eye tracking for the assessment of driver fatigue. *Healthcare Technology Letters*, *5*(2), 54–58. https://doi.org/10.1049/htl.2017.0020

Xu, X.-W., Liu, C.-R., Yu, X.-J., Xiong, H., & Qian, F. (2020). Research on Fatigue Driving Detection Method Based on Lightweight Convolutional Neural Network. *2020 IEEE 5th International Conference on Intelligent Transportation Engineering (ICITE)*, 254–258. https://doi.org/10.1109/ICITE50838.2020.9231511

Yang, K., Wang, C., Sarsenbayeva, Z., Tag, B., Dingler, T., Wadley, G., & Goncalves, J. (2021). Benchmarking commercial emotion detection systems using realistic distortions of facial image datasets. *The Visual Computer*, *37*(6), 1447–1466. https://doi.org/10.1007/s00371-020-01881-x

Zhang, F., Mao, Q., Dong, M., & Zhan, Y. (2016). Multi-pose Facial Expression Recognition Using Transformed Dirichlet Process. *Proceedings of the 24th ACM International Conference on Multimedia*, 347–351. https://doi.org/10.1145/2964284.2967240

Zhang, F., Su, J., Geng, L., & Xiao, Z. (2017). Driver Fatigue Detection Based on Eye State Recognition. *2017 International Conference on Machine Vision and Information Technology (CMVIT)*, 105–110. https://doi.org/10.1109/CMVIT.2017.25

Zhang, J., Yin, Z., Chen, P., & Nichele, S. (2020). Emotion recognition using multi-modal data and machine learning techniques: A tutorial and review. *Information Fusion*, *59*, 103–126. https://doi.org/10.1016/j.inffus.2020.01.011

Zhang, L., Jiang, M., Farid, D., & Hossain, M. A. (2013). Intelligent facial emotion recognition and semantic-based topic detection for a humanoid robot. *Expert Systems with Applications*, *40*(13), 5160–5168. https://doi.org/10.1016/j.eswa.2013.03.016

Zhang, Z., Cui, L., Liu, X., & Zhu, T. (2016). Emotion Detection Using Kinect 3D Facial Points. *2016 IEEE/WIC/ACM International Conference on Web Intelligence (WI)*, 407–410. https://doi.org/10.1109/WI.2016.0063

Zheng, C., Xiaojuan, B., & Yu, W. (2016). Fatigue driving detection based on Haar feature and extreme learning machine. *The Journal of China Universities of Posts and Telecommunications*, *23*(4), 91–100. https://doi.org/10.1016/S1005-8885(16)60050-X

Zhuang, Q., Kehua, Z., Wang, J., & Chen, Q. (2020). Driver Fatigue Detection Method Based on Eye States With Pupil and Iris Segmentation. *IEEE Access*, *8*, 173440–173449. https://doi.org/10.1109/ACCESS.2020.3025818