Human Activity Recognition in a Car with Embedded Devices

Danilo Burbano and Jose Luis Carrera

***Abstract*—Detection and prediction of drowsiness is key for the implementation of intelligent vehicles aimed to prevent highway crashes. There are several approaches for such solution. In this paper the computer vision approach will be analysed, where embedded devices (e.g. video cameras) are used along with machine learning and pattern recognition techniques for implementing suitable solutions for detecting driver fatigue.**
Most of the research in computer vision systems focused on the analysis of blinks, this is a notable solution when it is combined with additional patterns like yawing or head motion for the recognition of drowsiness. The first step in this approach is the face recognition, where AdaBoost algorithm shows accurate results for the feature extraction, whereas regarding the detection of drowsiness the data-driven classifiers such as Support Vector Machine(SVM) yields remarkable results.
One underlying component for implementing a computer vision technology for detection of drowsiness is a database of spontaneous images from the Facial Action Coding System (FACS), where the classifier can be trained accordingly.
This paper introduces a straightforward prototype for detection of drowsiness, where the Viola-Jones method is used for face recognition and cascade classifier is used for the detection of a contiguous sequence of eyes closed, which are considered as drowsiness.

***Index Terms*—drowsiness, cascade classifier, Viola-Jones method, FACS, AU**

***Resumen*—La detección y predicción de la somnolencia es clave para la implementación de vehículos inteligentes destinados a prevenir accidentes en carreteras. Existen varios enfoques para crear este tipo de vehículos. En este artículo se analiza el enfoque de visión por computador, donde dispositivos embebidos son usados conjuntamente con técnicas de inteligencia artificial y reconocimiento de patrones para implementar soluciones para la detección del nivel de fatiga de un conductor de un vehículo. La mayoría de investigaciones en este campo basados en visión por computador se enfocan en el análisis del parpadeo de los ojos del conductor, esta solución combinada con patrones adicionales como el reconocimiento del bostezo o el movimiento de la cabeza constituye ser una solución bastante eficiente. El primer paso en este enfoque es el reconocimiento del rostro, para lo cual el uso del algoritmo AdaBoost muestra resultados precisos en el proceso de extracción de características, mientras para la detección de somnolencia, el uso de clasificadores como el Support Vector Machine (SVM) muestra también resultados prometedores.**
Un componente básico en la tecnología de visión por computador es el uso de una base de datos de imágenes espontaneas acorde al Sistema Codificado de Acciones Faciales (SCAF), con la cual el clasificador puede ser entrenado. Este artículo presenta un prototipo sencillo para detección de somnolencia, en el cual el método de Viola-Jones es utilizado para el reconocimiento de rostros y un clasificador tipo cascada es usado para la detección de ojos cerrados en una secuencia continua de imágenes lo que constituye un indicador de somnolencia.

***Palabras clave*—somnolencia, clasificador tipo cascada, método Viola-Jones, SCAF**

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I. Introduction

THERE are several human factors that causes highway crashes and vehicle collisions, one of them is driver drowsiness or fatigue. With the active intelligent vehicles research and last advances in embedded devices, the implementation of human activity recognition mechanisms aimed to prevent such accidents are becoming a subject of big interest, because it will transform positively the way drivers interact with their vehicles.
Automatic driver fatigue detection with embedded devices is one technology that can be used to achieve this, which is the main subject of this paper. Driver fatigue detection refers to the use of machine learning and pattern recognition techniques in order to determine the driver's fatigue level, whereas embedded devices refers to sensors used to gather and monitor the required data from the vehicle or the driver. By integrating these techniques, enough information for an accurate estimation of the driver's state is obtained.

A. Driver Fatigue Detection and Prediction

The mechanisms used to recognize driver fatigue, should focus not only on detecting but also on predicting driver drowsiness, so that they can really avoid potential vehicle collisions. There are some technologies identified as in [1], [2] which categorizes these solutions in four main groups described below:

1) Fitness for duty technologies: These technologies are intended to provide some behavioural or biological estimate of an operator's functional capability for work yet to be performed relative to a standard [2]. Thus most solutions are based on assessing the vigilance or alertness capacity of an operator before the work is performed. Performance of the subject at a chosen task is used as a measure to detect existing fatigue impairment. This approach involves eye hand coordination or driving simulator tasks methods, as well as sampling aspects of performance capability or physiological response.
Fitness for duty solutions are potentially good for measuring existing fatigue, but have rather dramatic learning curves,

additionally they are aptitude and language skill sensitive making their predictive validity still not well known.

2) Mathematical models of alertness dynamics: This approach uses mathematical models in order to predict the performance of an individual based on past sleep and workload factors. For instance an integration of the model is into a wrist-activity monitor and recorder which will store up records of the wearer's activity and sleep obtained over several days. This models show potential to easily predict fatigue in drivers but a large amount of validation and possible fine tuning of the models are needed before they can be fully accepted.

3) Vehicle-based performance technologies: These technologies are directed at measuring the behaviour of the transportation hardware systems under the control of the driver. Vehicle-based performance technologies places sensors on standard vehicle components, e.g., steering wheel, gas pedal, and analyses the signals sent by these sensors to detect drowsiness, under the assumption that it reflects identifiable alterations when the driver is fatigued. This approach is clearly a non-intrusive one, which is an advantage, but work in very limited situations and its implementation is complex.

4) In-vehicle, on-line, operator status monitoring technologies: These set of techniques are aimed to measure the behaviour of the driver. Several types of measurements are employed for acquiring the required data like video of the face (eyelid position, eye blinks, eye movements, pupil activity, facial tone, direction of gaze, head movements), eye trackers, wearable eyelid monitors, head movement detector, EEG[1] and ECG[2] devices. There are mainly two approaches used under this context:
i) Physiological Signals, ii) Computer Vision Systems. The former focus on the measurement of physiological signals such as heart rate, pulse rate and EEG. However this method has drawbacks in terms of practicality since it requires a person to wear an EEG cap while driving. The latter is a prominent technology in monitoring the operator status and a non-intrusive one, the remaining sections of this paper as well as our prototype will be based on this approach.

In this paper a description of the steps used for the implementation of a small prototype which detects fatigue and drowsiness using the computer vision approach will be made, where the Cascade classifier will be used for the face detection and drowsy driver detection as well.

II. Related Work

The studies done for detection of fatigue and drowsiness using the computer vision approach are focused mainly in the analysis of blinks, but there are also research works that incorporate additional facial expressions or human behaviour for drowsy driver detection.
Previous works as in [4] implemented a semi-automated eye tracking system that analyses measures associated with slow eye closure, based in video monitoring and applying a scientifically supported method known as PERCLOS (Percent Eyelid Closure). Some of these works used infrared cameras to estimate the PERCLOS measure. It is worth pointing out that infrared technology for PERCLOS measurement works fairly well in the darkness of night, but not very well in daylight, because ambient sun light reflections make it impractical to obtain retinal reflections of infrared [1]. Subsequent researches as in [5] used enhanced versions of the PERCLOS cameras, known as Copilot the second generator of PERCLOS monitor, which uses a structured illumination approach to identifying a driver's eyes.
Computer vision researches not only focus on blink rate for drowsiness, some studies as in [1] and [3] include eye closure, yawing and even head motion for the analysis. These works use machine learning techniques such as Adaboost [12] for the feature selection and SVM to detect the facial actions, achieving an accuracy of 96%. The studies shows significant associations between facial expression and fatigue beyond eye blinks, interesting findings like the fact that in 60 seconds before falling asleep, drivers yawn less, not more as is often thought, were done. This kind of studies are based upon important works as in [6] where detection of facial actions from spontaneous facial expressions were established through the implementation of FACS (Facial Action Coding System), this drove another studies for establishing suited datasets of FACS as [7] where a database of digitized images were constituted by performing multiple tokens of most primary FACS action units on several subjects of varying ethnicity. An interesting work for establishing a dataset of FACS is found in [11], where besides AU (Action Units), Lucey et al. define a set of Emotions in terms of these facial action units.
Considering a real time solution for drowsy driver detection requires in first place mechanisms for face detection of the driver, as in [8] which uses a probabilistic model learned using boosting methods, where the system is robust enough to detect differences in facial structure, including facial expressions and eyeglasses. Another interesting research as in [9] uses algorithms for face detection which are able to work in an unconstrained environment, where a modified Adaboost algorithm and Cascade classifier methods are used for a robust real time face detection.
The goal of this paper is to evaluate the cascade classifier used in Viola Jones algorithm to detect action units related to drowsiness in drivers. This is the first paper as far as we know, that evaluates the Viola Jones algorithm as a possible mechanism to detect drowsiness. The remaining sections of this paper are as follows: In section 3 a detailed overview of the Computer Vision Systems methods for drowsy driver detection along with FACS is presented, in section 4 the machine learning techniques used for the face and drowsiness detection are explained, finally in section 5 the implementation of the prototype is introduced along with its results and evaluation.

[1] EEG (Electroencephalography) is the recording of electrical activity along the scalp.

[2] ECG (Electrocardiography) is the recording of the electrical activity of the heart.

III. Computer Vision Systems

Computer vision is a prominent technology in monitoring the driver status. It is useful in detecting and recognizing the facial motion and appearance changes occurring during drowsiness. The advantage of computer vision techniques is that they are non-invasive, and thus are more amenable to use by the general public [1].

A. Face Detection

Face detection is a computer vision technology aimed to detect human faces features in an image ignoring anything else. There are several approaches to perform face detection, most of which deals with faces at arbitrary scales assuming upright faces [10]. One of the most used mechanisms for face detection is the Haar Feature-Based Cascade classifier [9], also known as Viola-Jones method. This approach combines four key concepts for detecting objects in images:

- Simple rectangular features, called Haar features.
- An Integral Image for rapid feature selection.
- The AdaBoost machine-learning method.
- A cascade classifier to combine many features efficiently.

Viola-Jones method is suitable for real-time recognition, because it is faster than any of their contemporaries [10].

B. Facial Action Coding System

Facial action coding system (FACS) are objective coding standards developed by behavioural scientists which captures the richness and complexity of facial expressions, which provides a general purpose representation that can be useful for many applications, thus it has been widely applied for computer vision systems aimed to recognize drowsiness or fatigue in drivers.
FACS provides an objective and comprehensive language for describing facial expressions, allowing the discovery of new patterns related to emotional or situational states. FACS has also been able to identify patterns of facial activity involved in alcohol intoxication that observers not trained in FACS failed to note [6].
FACS can be seen as a general database of coded human facial expressions composed of action units (AU) as shown in figure 1, where the application of computer vision mechanisms enabled the automatic coding of facial expressions providing data on the dynamics of facial behaviour at a resolution that was previously unavailable, making facial expressions measurable.

C. Workflow for FACS

Most of the implementations done for real time automated recognition of facial actions from the facial action coding systems as in [1] and [6], uses a process similar as the one illustrated in figure 2, where the first input is a video of the person, from which face and eyes detection algorithms are applied in real time, then the automatically detected faces are aligned based on the detected eye positions, cropped, scaled and then passed through a bank of Gabor filters using AdaBoost for the feature selection. Afterwards these outputs (i.e. filters selected by AdaBoost) are normalized and then passed to a standard classifier, like SVM which is trained for each of the AU (i.e. facial actions) which are considered as prediction for drowsiness, for instance the ones showed in table I.
The machine learning techniques used for automatic face and eyes detection, feature selection, and data-driven classifiers[3] could vary depending on the requirements. Barlett et al. [6] compared some machine learning algorithms using this workflow, and reported that the best results were obtained through the association of the techniques showed in figure 2. In this paper, the Cascade classifier will be used for the face detection and also used as the classifier trained for the AU considered as prediction for drowsiness.

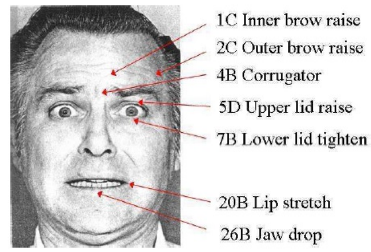

Fig. 1. Example facial action decomposition from the Facial Action Coding System with seven Action Units [6].

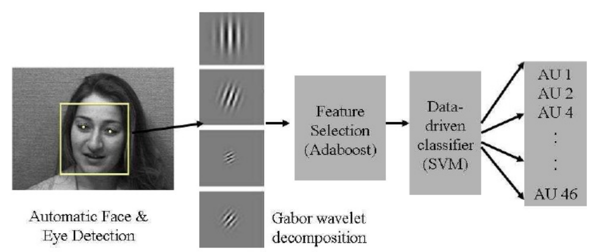

Fig. 2. Overview of fully automated facial action coding system [6].

IV. Machine Learning and Pattern Recognition Techniques

The techniques described in this paper are the ones used for the implementation of the prototype.

A. Viola-Jones Method

The basic principle of the Viola-Jones algorithm is to scan a sub-window capable of detecting faces across a given input image [9]. Viola and Jones use a classifier that, largely for the sake of computational efficiency, is based on an attentional cascade. The individual weak classifiers are based on a variant of the AdaBoost algorithm, which converts weak classifiers into a strong classifier via boosting. To be detected, an image must be detected by each level of a series of basic classifiers, each more discriminating than the last.

[3] data-driven classifiers describe the data to be matched

TABLE I
AN EXAMPLE OF A SET OF AU USED FOR PREDICTING DROWSINESS [1].

AU	Name
1	Inner Brow Raise
2	Outer Brow Raise
4	Brow Lowerer
5	Upper Lid Raise
6	Cheek Raise
7	Lids Tight
8	Lip Toward
9	Nose Wrinkle
10	Upper Lip Raiser
11	Nasolabial Furrow Deepener
12	Lip Corner Puller
13	Sharp Lip Puller
14	Dimpler
15	Lip Corner Depressor
16	Lower Lip Depress
17	Chin Raise
18	Lip Pucker
19	Tongue show
20	Lip Stretch
22	Lip Funneller
23	Lip Tightener
24	Lip Presser
25	Lips Part
26	Jaw Drop
27	Mouth Stretch
28	Lips Suck
30	Jaw Sideways
32	Bite
38	Nostril Dilate
39	Nostril Compress
45	Blink

The computational advantage is gained in the fact that the initial levels of the cascade can use very simple features for their classifiers, and therefore can reject the vast majority of locations in an image quickly [10]. There are three main steps to follow for applying this method, which are described below:

1) Integral Image: The first step of the Viola-Jones face detection algorithm is to turn the input image into an integral image. This is done by making each pixel equal to the entire sum of all pixels above and to the left of the concerned pixel [9], as is illustrated in figure 3, where positive and negative images are used to train the classifier.

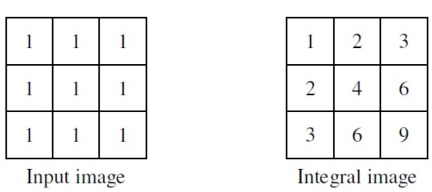

Fig. 3. The integral image [9].

2) Sum Calculation: The value of the sum of all pixels inside any rectangle can be done using only the values of the pixels that coincide with the corners in the input image, as is illustrated in figure 4.

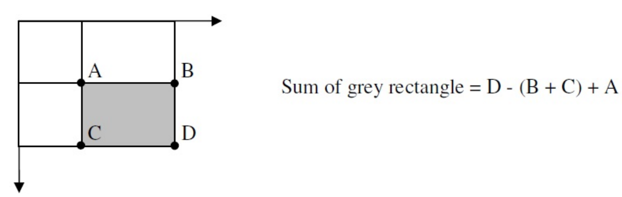

Fig. 4. Sum calculation into an integral image [9].

3) Feature Extraction: There are five types of features (reminiscent of Haar wavelets) defined, which consists of two or more rectangles. Each feature value is obtained by subtracting sum of pixels under the white rectangle from sum of pixels of black rectangle as illustrated in figure 5.
All possible sizes and locations are used to calculate features in the detector, this will result in over 160.000 features [9], where the best features are selected.

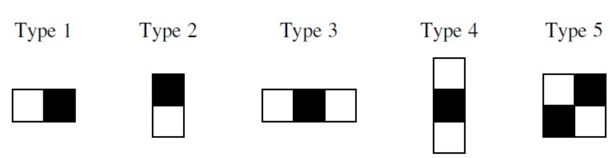

Fig. 5. Different types of features [9].

The tree steps stated above are all typically combined in a single schema so-called Scale Invariant Detector.

B. AdaBoost

AdaBoost is a machine learning boosting algorithm capable of constructing a strong classifier through a weighted combination of weak classifiers[4], where each feature is considered to be a potential weak classifier.
Applying to face detection, the goal of AdaBoost is to smartly construct a mesh of features capable of detecting faces. As stated above there can be calculated approximately 160.000 feature values within a detector at base resolution. Among all these features some few are expected to give almost consistently high values when on top of a face. In order to find these features Viola-Jones use a modified version of the AdaBoost algorithm. Since only a small amount of the possible 160.000 feature values are expected to be potential weak classifiers the AdaBoost algorithm is modified to select only the best features, where the best performing feature is chosen based on the weighted error it produces. This weighted error is a function of the weights belonging to the training examples.
As a result the weight of a correctly classified example is decreased and the weight of a misclassified example is kept constant, thus the second feature is forced to focus harder on the examples misclassified first [9].

C. Cascade Classifier

The cascaded classifier is composed of stages each containing a strong classifier. Applying to face detection, the job of each stage is to determine whether a given sub-window is definitely not a face or maybe a face. It is faster to discard a non-face than to find a face, therefore instead of finding faces, the algorithm should discard non-faces. With this in mind a detector consisting of only one strong classifier suddenly seems inefficient since the evaluation time is constant no matter the input. Hence the need for a cascaded classifier arises [9].
The approach is illustrated in figure 6, where features are grouped into different stages of classifiers and apply them one-by-one. Then if the detector fails in the first stage, this is discarded and the remaining features will be not considered.

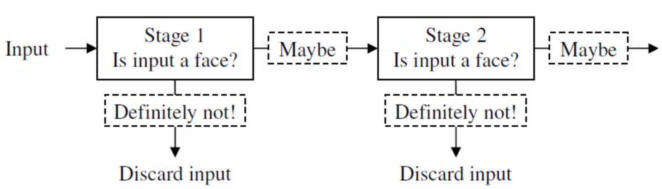

Fig. 6. The cascade classifier [9].

Regions of the image suspected to contain faces will have more attention.
The same principle is applied in the prototype for detection of drowsiness, where the AU "eyes closed" is discarded by each stage, as showed in figure 7.

[4]Weak classifiers classify correctly in only a little bit more than half of the cases.

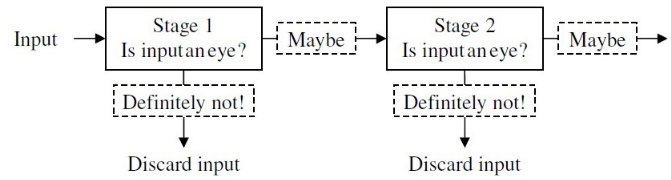

Fig. 7. The cascade classifier for the AU "eyes closed".

V. PROTOTYPE

The main idea of the prototype is to simulate a real life scenario of a driver, thus the video camera of a computer is used to capture in real time the face of a person, and determine based on his eyes drowsiness. For achieving this, the prototype presents an automatic drowsy driver monitoring as showed in figure 8, where the system is based on tracking the changes in the eye blink duration by calculating eyes opening percentage (EOP) to launch an alarm when the system detects a drowsy driver.

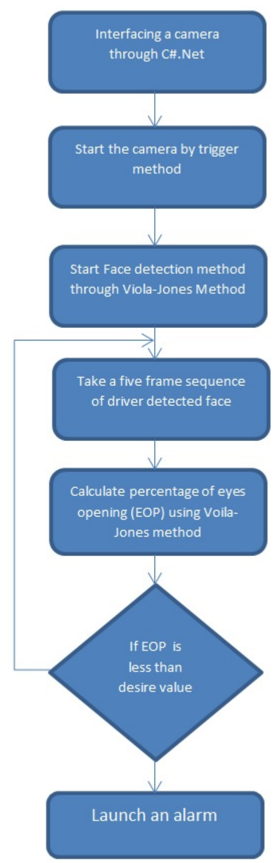

Fig. 8. Flow Chart of the Prototype

The prototype was done using the Cascade classifier for the face detection, based on XML descriptors which were built using AdaBoost frontal face detector, whereas for the detection of drowsiness the prototype uses a dataset of vector of features in XML format. Afterwards these vectors of features are also passed to a Cascade classifier, where one

TABLE II
ACTION UNITS USED FOR THE EVALUATION OF THE PROTOTYPE.

Eyes Opened	10639
Eyes Closed	69
Total	10708

TABLE III
RESULTS OF DETECTION OF EYES CLOSED USING CASCADE CLASSIFIER WITH 69 EXPRESSIONS WITH EYES ACTUALLY CLOSED.

Opened	10
Closed	59
Error rate	0.1449

TABLE IV
RESULTS OF DETECTION OF EYES OPENED USING CASCADE CLASSIFIER WITH 10639 EXPRESSIONS WITH EYES ACTUALLY OPENED.

Opened	8458
Closed	2181
Error rate	0.2050

straightforward AU “Eyes Closed” is used as a prediction for drowsiness.

A. Evaluation

An evaluation of the cascade classifier used in the prototype was done with a set of pictures, the algorithm was tested using the Extended Cohn-Kanade (CK+) database which consists of 593 expressions from 123 subjects with FACS [14], which include both posed an spontaneous expressions. For this prototype the AUs taken into account are shown in table II where it is possible to verify that a total of 10708 pictures where available to use for testing.

Table III shows the test results for the AU Eyes Closed, where the error rate is 14.49%, whereas the error rate for the AU Eyes Opened is 20.50% as shown in table IV. These result reflect that the algorithm has better accuracy for the AU eyes closed, nevertheless it would be advisable to test the results with more AU with eyes closed, to have a more realistic estimation, where according to this evaluation it would be expected to have an error rate of around 14%.

In order to assess the accuracy of the whole prototype, the precision was calculated using the formula 1, where the true positives and false positives are considered as measure, where the former is the number of times the algorithm recognised as opened the AU Eyes Opened or as closed the AU Eyes Closed, and the latter is the number of times the algorithm recognised as opened the AU Eyes Closed or closed the AU Eyes Opened. At the end the algorithm had an accuracy of 79.54% which is a reasonable precision for a small prototype, in addition this evaluation shows that the cascade classifier could be used for the recognition of AU such as eyes closed or eyes opened.

$$\frac{nbtruepositive}{nbtruepositive + nbtruenegative} \tag{1}$$

TABLE V
ACCURACY EVALUATION

Classifier	Recognition Rate
Bayes	75.57%
Neural Networks	76.89%
SVM	85.34%
Cascade Classifier	79.54%

Additionally the vectors of features generated from the feature extraction algorithm were used for training the most common classifiers.

$$x^{(AU)} = [Z_1, Z_2, Z_3, ..., Z_4] \tag{2}$$

By taking all the vectors as showed in 2, a dataset was built and applied directly to Weka for comparing the accuracy, as can be seen in table V.
Results show that Viola Jones method has more accuracy than Bayes and Neural Network machine learning algorithms, however the accuracy for SVM is better than Viola Jones but at the same time more complex to implement and it takes more computing resources to execute (i.e. computing expensive).

VI. CONCLUSION AND FUTURE WORK

Spontaneous expressions differ from posed expressions, thus a database of spontaneous facial expressions to train and evaluate systems for automatic recognition of facial expressions would be the best as it would give results closer to real life scenarios. The studies made for recognition of drowsiness based on facial expressions have more accurate results when are used along with another additional pattern like head motion. This fact shows that by including additional parameters like heart rate, head motion, voice tone, etc. for training the classifier, the results could be even better, thus as a future work, it would be very interesting to include such measures (using others embedded devices for gathering the required data) to assess the expectations of reduction in the error rate.
An algorithm for feature selection that is definitely suitable for evaluating and analysing human faces is AdaBoost, as showed in previous studies [6] this algorithm enhanced both speed and accuracy of SVM regarding the detection of a facial action (i.e. action unit), whereas for face recognition when AdaBoost is used in the Viola-Jones method the results are very efficient. The classifiers used for the task of facial action recognition can vary but the best results are with the data-driven ones.
Using emotions instead of just AU could be an interesting work to develop human activity recognition applications, where emotions such as angry, anxiety could trigger an alert for drivers, or recognise states like drunk, which could yield some instructions to the intelligent vehicle, so that it does not start working.

Based on the analysis and results of these studies, it would be possible to state that real applications of these technologies should have at least the characteristics below:

- A database fully FACS coded from spontaneous expressions.

- Using AdaBoost algorithm (or similar) for the feature extraction along with a data-driven classifier.
- Additional patterns to take into account like head motion, heart rate, etc.

Regarding the prototype, as a future work it would be also interesting to try to increase the accuracy not only by including additional parameters for training the classifier, but also to find out some variant of the cascade classifier algorithm and evaluate it with additional AU in an attempt to identify the ones with high accuracy for this classifier.

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