

## DETECTION OF DRIVER SLEEPINESS AND WARNING THE DRIVER IN REAL-TIME USING IMAGE PROCESSING AND MACHINE LEARNING TECHNIQUES

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### ABSTRACT

The aim of this study is to design and implement a system that detect driver sleepiness and warn driver in real-time using image processing and machine learning techniques. Viola-Jones detector was used for segmenting face and eye images from the camera-acquired driver video. Left and right eye images were combined into a single image. Thus, an image was obtained in minimum dimensions containing both eyes. Features of these images were extracted by using Gabor filters. These features were used to classifying images for open and closed eyes. Five machine learning algorithms were evaluated with four volunteer's eye image data set obtained from driving simulator. Nearest neighbor IBk algorithm has highest accuracy by 94.76% while J48 decision tree algorithm has fastest classification speed with 91.98% accuracy. J48 decision tree algorithm was recommended for real time running. PERCLOS the ratio of number of closed eyes in one minute period and CLOSDUR the duration of closed eyes were calculated. The driver is warned with the first level alarm when the PERCLOS value is 0.15 or above, and with second level alarm when it is 0.3 or above. In addition, when it is detected that the eyes remain closed for two seconds, the driver is also warned by the second level alarm regardless of the PERCLOS value. Designed and developed real-time application can able to detect driver sleepiness with 24 FPS image processing speed and 90% real time classification accuracy. Driver sleepiness were able to detect and driver was warned successfully in real time when sleepiness level of driver is achieved the defined threshold values.

**Keywords:** driver, sleepiness, real time, image processing, machine learning.

### INTRODUCTION

According to a report published by the American Automobile Association (AAA) Foundation of Traffic Safety, 41% of drivers are have dosed off or nodded off due to sleepiness while driving. It is also stated that 16.5% of the accidents resulting in death and injury were caused by tired and sleepy drivers [1]. Among respondents who fell asleep, the median prevalence of sleep-related accidents was 7.0% (13.2% involved hospital care and 3.6% caused fatalities) [14].

According to the results of the study performed for commercial vehicle drivers in Edirne district of Turkey, 22 out of 138 drivers (15.9%) have experienced or survived a risk of at least one traffic accident due to sleepiness [20]. According to the results of a similar study involving Edirne and Hatay districts, 49 out of 320 drivers (15.3%) had or survived the risk of at least one accident due to sleepiness [19]. As a result of a questionnaire survey on commercial drivers, it is concluded that in 17% of drivers having an accident, the accidents were caused by sleepiness [21].

It is envisaged that a system in the vehicles which recognizes sleepiness states of drivers and warns the driver can significantly reduce the traffic accidents that may occur due to fatigue and sleepiness [5, 7, 11, 13].

In this study, it is aimed to design and implement a system which discerns the sleepiness level of the driver and if sleepiness is detected, recommends the driver to stop and rest by a warning system, by using real time image processing techniques and machine learning algorithms.

### MATERIAL AND METHOD

In this study, real-time camera image data of four volunteers were used to test the driver's sleepiness. Camera images are taken from a driving simulation. The driver images taken were reduced to 320x240 spatial resolution and converted to gray scale with the formula shown in Equation 1.

$$Y = 0,2126 \cdot R + 0,7152 \cdot G + 0,0722 \cdot B \quad (1)$$

In this Equation, Y represents pixel brightness, R is red, G is green and B is blue color brightness. Since color information is not used in



Fig. 1. Applying Haar-like features to the a face image

the image processing algorithms to be used, only the gray scale image is processed.

The face and eye images of the driver are detected and cropped by the Viola-Jones detector method. The Viola-Jones detector is an AdaBoost classifier that uses Haar-like features. AdaBoost classifiers train T amount of  $h_t$  weak classifiers which usually consist of independent and single level binary decision trees. An  $\alpha_t$  weight value is given for each classifier. As the input data set,  $x_i$  feature vectors labeled with a  $y_i$  binary tag are used, each of which is only -1 and +1. Finally, the class of the  $x_i$  input is calculated by Equation 2 [3].

$$H(x) = \text{sign} \left( \sum_{t=1}^T \alpha_t h_t(x) \right) \quad (2)$$

In this equation, H(x) is the class of the x sample,  $h_t$  is the weak classifier, and  $\alpha_t$  is the classifier coefficient. The Sign function returns 1 for all positive values and -1 for all negative values. Zero values returned as zero. An example showing the application of Haar-like features to the facial image is shown in Figure 1.

After finding the facial image, the left and right eye areas were cropped using the geometric ratios of the face and the left and right eye images were simultaneously found in these areas using parallel tasks [2]. The eye images were combined to obtain a minimum size image containing both eyes. 40 Gabor filters were used at eight different angles and five different scales to extract the features of these images. Gabor filters define sine and cosine functions within a Gaussian window. Two dimensional Gabor wavelets are obtained by using two dimensional forms of these functions. The real (even) and imaginary (odd) components of two-dimensional Gabor wavelets are denoted by Equation 3 and Equation 4, respectively [4, 8].

$$g_e(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} \cdot e^{-\frac{1}{2} \left( \frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2} \right)} \cdot \cos(2\pi\omega_{x0}x + 2\pi\omega_{y0}y) \quad (3)$$

$$g_o(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} \cdot e^{-\frac{1}{2} \left( \frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2} \right)} \cdot \sin(2\pi\omega_{x0}x + 2\pi\omega_{y0}y) \quad (4)$$

In these equations, the  $g_e$  function is the real (even) component, and the  $g_o$  function is the virtual (odd) component. The Gabor wavelets used to extract the feature in this study are shown in Figure 2.

When Gabor wavelets are applied to the image by convolution, a resulting response image is obtained. The visual feature value for each Gabor wavelet is obtained by calculating the energy levels of these response images with the formula shown in Equation 5.

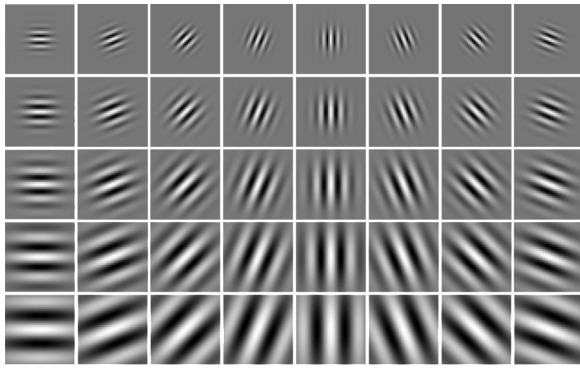


Fig. 2. Gabor wavelets at eight different angles and five different scales

$$E = \sum_{x=0}^{w-1} \sum_{y=0}^{h-1} I(x,y)^2 \tag{5}$$

In this equation, E is the energy level, x and y are the pixel coordinates, w and h are the image width and height, respectively. The function I(x,y) is the brightness value of the pixel at points x and y.

Four different data sets were obtained by extracting the features of 1077 images of classified open and closed eyes belonging to four volunteers with 40 Gabor wavelets. In order to improve the real-time classification performance, the feature selection was made according to the correlation values and it was seen that 13 features with the highest correlation out of 40 features were tested to be sufficient for classification without lowering the accuracy.

Data sets were tested using five different machine learning algorithms with parametric variations. Weka application was used to test machine learning algorithms [15]. The accuracies obtained

for each data set from the test are shown in Table 1. In the Table, the highest two values for each column are written in bold.

When the accuracies of the machine learning algorithms are examined, it is observed that the nearest neighbor IBk algorithm gives the highest accuracy in all data sets. However, classification speeds have also been evaluated to see if the algorithms are suitable for real-time operation. The classification speeds obtained are shown in seconds in Table 2. In this table, the lowest two values for each column are written in bold.

According to classification speeds, the fastest classifier seems to be the J48 decision tree. The classification speed of the IBk algorithm, which gives the highest accuracy value at 94.76%, is an average of 147 milliseconds. The decision tree J48 algorithm has an average classification speed of 3 milliseconds with an accuracy of 91.98%.

The total duration of the spontaneous closing and opening phases of the human eyelid is approximately 334 milliseconds [23]. The classification speed of the IBk algorithm is almost half the speed of the blink time. However, the J48 decision tree has more than enough speed to catch an eye blink easily. For this reason, we concluded that the J48 algorithm, which is 2.78% lower in accuracy, is suitable for real-time classification.

A real-time software has been developed for detection of driver drowsiness using personal data. This software classifies the eyes as open or closed by cropping the driver’s face and eye images in a real-time video image through the model trained beforehand by machine learning algorithms. Open and closed eyes are recorded on an array during

Table 1. Truth values of machine learning algorithms according to data sets

Algorithm	Parameters	Accuracy (%)				
		A	B	C	D	Average
<b>Naïve Bayes</b>		96,02	96,59	88,66	91,66	93,23
<b>IBk</b>	1 neighbor	93,92	96,96	90,74	94,23	93,96
	5 neighbor	94,88	97,03	92,52	94,60	94,76
	10 neighbor	95,11	97,57	92,08	94,23	94,75
<b>J48</b>	Pruned	92,01	95,90	87,49	92,51	91,98
	Binary Tree	92,01	95,90	87,49	92,51	91,98
<b>SVM</b>	Linear Kernel	64,85	85,08	67,20	58,49	68,90
	Polynomial Kernel	83,57	96,24	69,05	88,54	84,35
	RBF Kernel	55,27	66,90	52,89	55,43	57,62
<b>Voted Perceptron</b>	1 iteration	84,53	92,87	52,89	77,20	76,87
	3 iteration	87,16	93,62	52,74	80,57	78,52
	5 iteration	87,57	94,00	52,66	82,86	79,27

**Table 2.** Classification times in seconds of machine learning algorithms according to data sets

Algorithm	Parameters	Classification Time (sec.)				
		A	B	C	D	Average
Naïve Bayes		0,036	0,057	0,05	0,039	0,046
IBk	1 neighbor	0,103	0,124	0,081	0,159	0,117
	5 neighbor	0,091	0,19	0,131	0,182	0,149
	10 neighbor	0,101	0,199	0,152	0,233	0,171
J48	Pruned	0,003	0,004	0,006	0,001	0,004
	Binary	0,001	0,002	0,001	0,002	0,002
SVM	Linear Kernel	0,01	0,013	0,01	0,033	0,017
	Polynomial Kernel	0,01	0,008	0,018	0,012	0,012
	RBF Kernel	0,16	0,332	0,316	0,467	0,319
Voted Perceptron	1 iteration	0,007	0,012	0,01	0,021	0,013
	3 iteration	0,006	0,024	0,028	0,023	0,02
	5 iteration	0,014	0,018	0,031	0,038	0,025

measurements made over a period of one minute. When the data in the array is complete, the PERCLOS (Percentage of Closure) value is calculated using the formula shown in Equation 6.

$$PERCLOS = \frac{1}{N} \cdot \sum_{i=0}^N f(i), f(i) = \begin{cases} 1, S_i < 0 \\ 0, S_i \geq 0 \end{cases} \quad (6)$$

In this equation, N is the number of samples, S is the sequence in which eye states are recorded. 1 is recorded for the open eye and -1 for the closed eye on the status array. The PERCLOS value is used for the two-level warnings. The PERCLOS threshold values for the warning levels are shown in Table 3.

Within one minute period, if the PERCLOS value is equal or greater than 0.15, the driver is warned with the first level warning; if the PERCLOS value is equal or greater than 0.3, the driver is warned by the second level warning. In addition, when it is detected that the eyes are closed for two seconds consecutively (CLOSDUR ≥ 2), the driver is warned by the second level alarm regardless of the PERCLOS value [12, 18]. The flow chart showing the decision process used

**Table 3.** PERCLOS threshold values used for the warning the driver

PERCLOS	Status of Driver	Warning Level
0,0 – 0,15	Attentive	No warning
0,15 – 0,30	Un-attentive	1. level warning, rest recommended
0,30 or more	Sleepy	2. level warning with higher level sound

for the warnings and driver warning messages is shown in Figure 3.

## RESULTS AND CONCLUSION

In this study, the real-time video images of the driver are cropped with the Viola-Jones by detecting face and eye images. Cropped eye images are classified as open or closed with machine learning algorithms. The values of PERCLOS and CLOSDUR which show the closure ratio of the eyes within period and closed eye duration values are calculated. If the PERCLOS value is equal or greater than the threshold value 0.15, the driver is warned with the 1st level warning, if the value is equal or greater than the 0.3 threshold value, the driver is warned by the 2nd level warning. If the CLOSDUR value is 2 seconds or more, the driver is also warned by the 2nd level warning.

In real-time study tests, eye classification and drowsiness detection rate was measured as 24 FPS (Frame per Second). This operating speed is considerably higher than the speeds of the studies often referred to as real-time. Table 4 compares the FPS type operating speeds with similar studies that perceive driver drowsiness through image processing. The data in the table is sorted from high to low according to the FPS value.

According to the comparison result, it is seen that the operation speed obtained in this study is well above the real time operation speeds reported in similar studies.

A video image composed of 3477 frames recorded with various drowsiness levels in order to

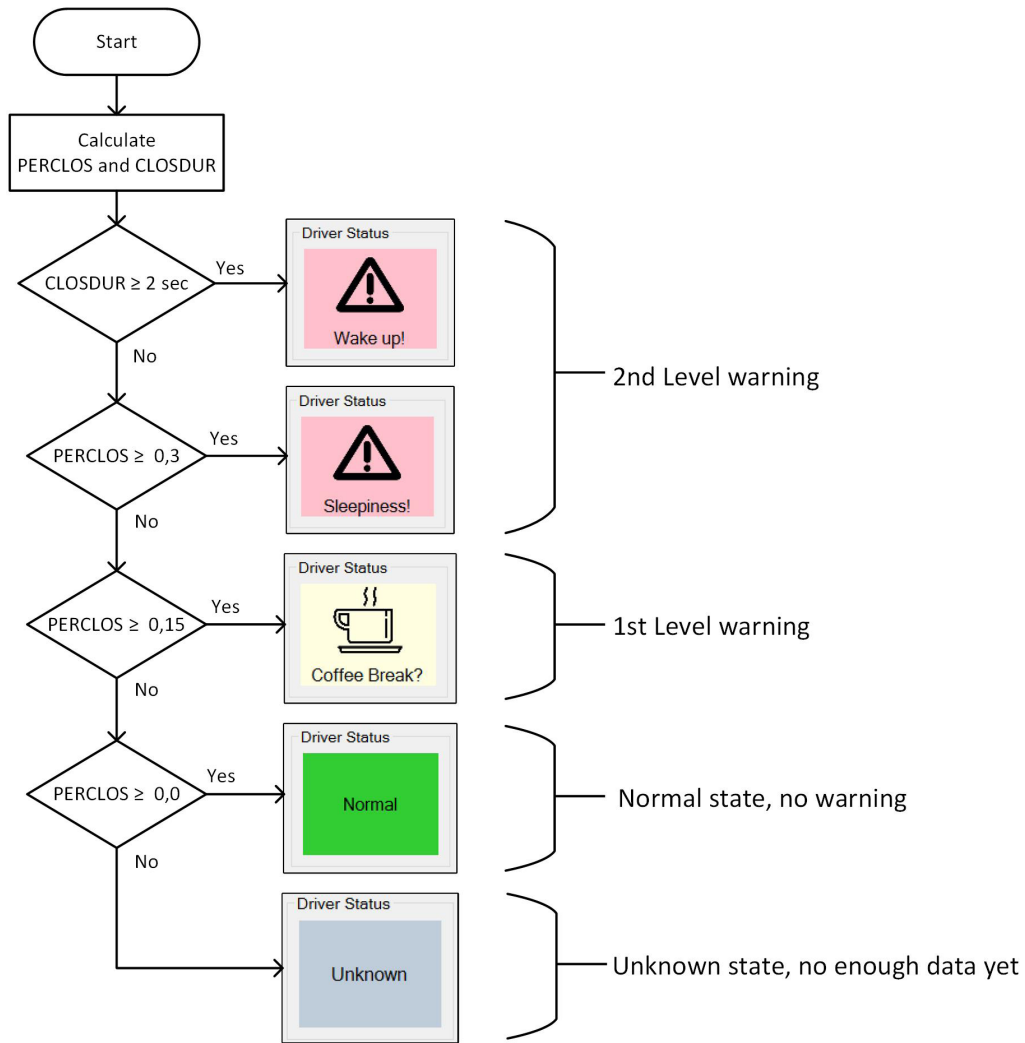


Fig. 3. Flow chart for the two-level driver warning system

Table 4. Comparing speed of application developed in this study with other similar studies

Reference	Image Processing Methods	Machine Learning Algorithms	Measured Behavior	Speed (FPS)
(*)	Gabor Filters	Naïve Bayes, IBk, J48, SVM, Voted Perceptron	PERCLOS CLOSDUR	24
[10]	Gabor filters	Principal Component Analyses (PCA), Hidden Markov Models (HMM)	Yawning	19
[16]	Viola Jones detector, Salient Point Analyses (SPA)	-	PERCLOS BLINK Yawning	16,5
[6]	Local Binary Pattern (LBP)	Support Vector Machines (SVM)	PERCLOS	12
[17]	Inverse Perspective Matching(IPM)	-	PERCLOS BLINKFREQ Road lanes	6
[9]	Principal Component Analyses (PCA)	Principal Component Analyses (PCA)	PERCLOS	6
[22]	Viola Jones detector, Blok Local Binary Pattern (LBP) histogram feature extraction	Statistical Learning (PLS), Support Vector machines (SVM)	PERCLOS	3

(\*) Real time application developed in this study.



**Table 5.** Confusion matrix obtained in the real-time operation test

		Classified Eyes	
		Open	Closed
Real State	Open	2271 (TP)	279 (FN)
	Closed	60 (FP)	867 (TN)

test the classification accuracy. For testing purposes, classified images were saved for counting the true and false classifications. The images classified during the test were visually inspected and the confusion matrix shown in Table 5 is obtained.

The performance results obtained from this confusion matrix are calculated as below: Accuracy: 0.90 TP rate: 0.89 FP rate: 0.06 Precision: 0.97 Recall: 0.89 Sensitivity: 0.89 Specificity: 0.94 F-Measure: 0.93

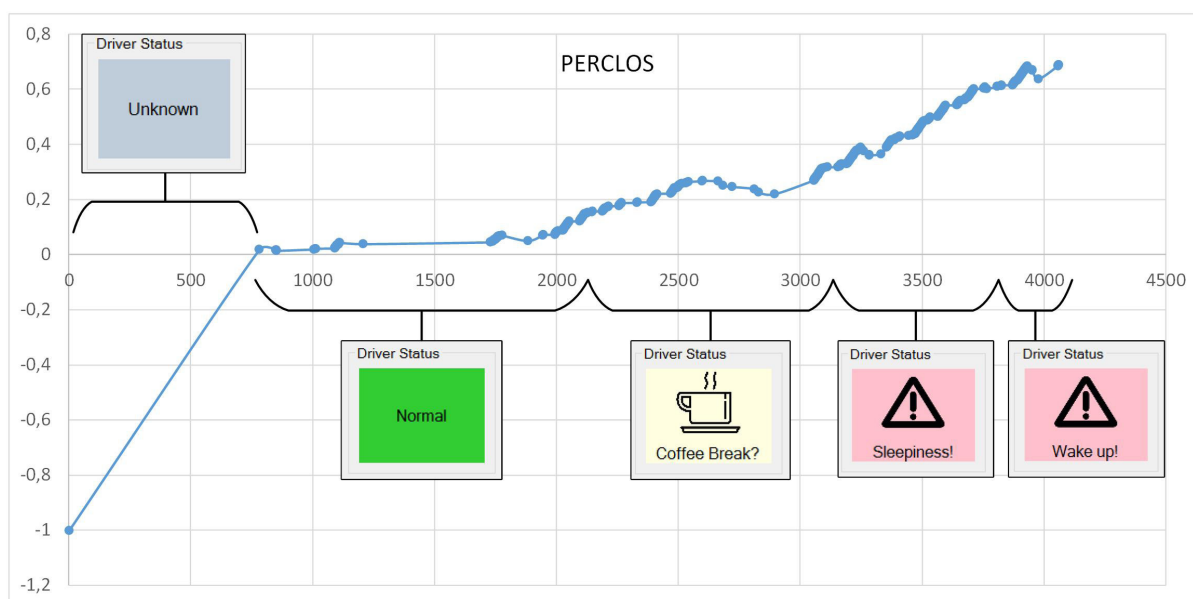
The accuracy obtained in real time operation is close to the accuracy value obtained from the data sets and the machine learning algorithms, but is slightly lower in accuracy value. Due to the different image conditions, a certain amount decrease of accuracy is common.

Alert points were marked by testing the driver warnings from the same video image on which the classification was tested. The moments that the driver is warned are shown in Figure 4.

In this video, the driver’s status is unknown for the first minute during the completion of the data in the array where the eye information is stored. The sleepiness state of the driver is indicated as normal and no warning is given until the 2113rd frame, until when the PERCLOS value does not exceed the threshold of 0.15. In between 2113rd to 3076th frames, the PERCLOS value has risen above 0.15, and the first level warning with a message suggesting that the driver take a break has been shown. After 3076th frame, due to increase in sleepiness, the PERCLOS value exceeded the threshold level of 0.3 and the driver was warned by the second level warning.

Along with the increase in the level of sleepiness, it has been observed that the duration of eye closing also increased. From the 3901st frame the CLOSDUR value has exceeded the threshold level of two, so that the eyes remaining closed for two seconds is determined and the driver is warned again with the second level warning.

As a result of the aim of operation of the application developed in consequence of this test, through this software developed by using the image processing techniques and machine learning algorithms in order to detect the driver’s drowsiness and to warn the driver, driver’s drowsiness was detected in real time at 24 FPS speed and 90% classification accuracy and the driver was warned. A screen capture of user interface of the developed application is shown in Figure 5.



**Fig. 4.** Warning messages given to the driver in return for increased PERCLOS value in real time video test. The horizontal axis indicates the frame number and the vertical axis indicates the PERCLOS value

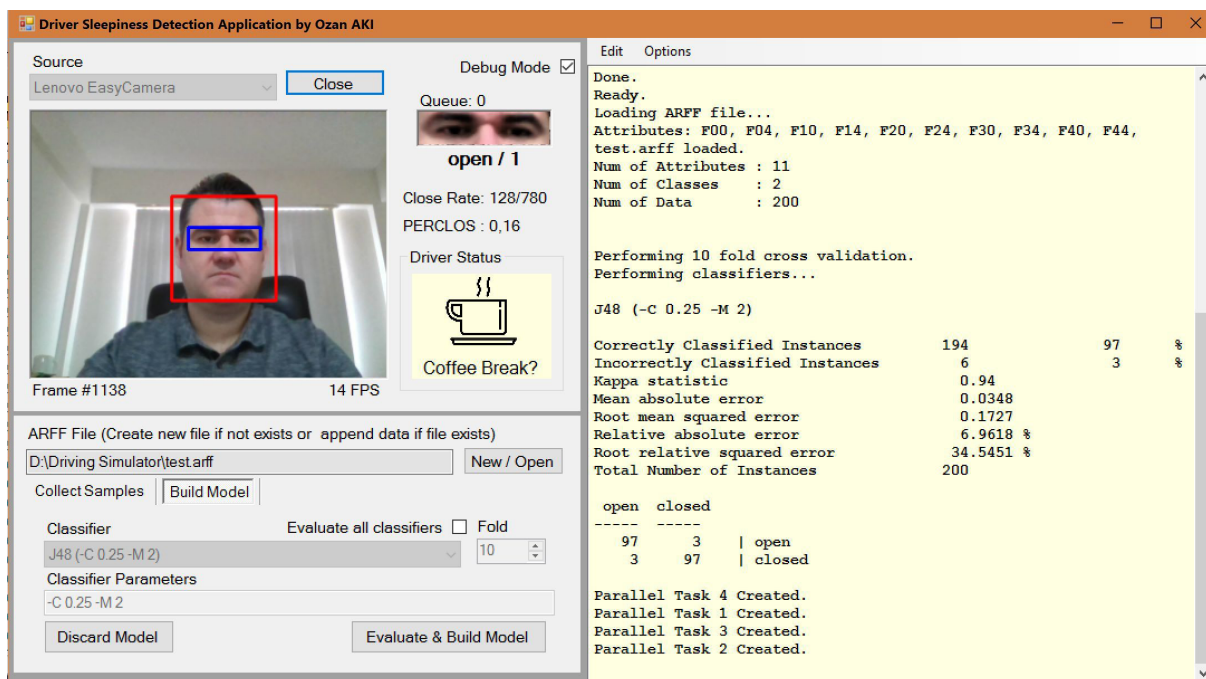


Fig. 5. Screen capture of user interface of developed software for detecting driver sleepiness

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