Driver Drowsiness Detection Based on Eye Movement and Yawning Using Facial Landmark Analysis

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***Abstract* - The drowsiness of the drivers can lead to road accidents. With the growth of computer vision and image processing technology it is now feasible to investigate this problem. This study aims to maintain driver's consciousness and detect drowsiness using a 300W dataset with the application of API Based Histogram of Oriented Gradients and Linear Support Vector Machine method. This enable face detection and classification, Random Forest Regression with 2 Node Splits for each tree for facial landmark, and Euclidean Distance points extraction for the eyes and mouth to detect drowsiness based on closing of the eyes and yawning. Our results show the model attained: i) a 91.67% accuracy rate performance in 0° degree camera angle, and ii) 93.33% accuracy in detecting drowsiness activity in both +45° to -45° camera angle, both in with 85% accuracy result in detecting both eye and mouth simultaneously.**

Keywords - driver's drowsiness, facial landmarks, eye detection, yawning detection

I. INTRODUCTION

In long distance rides, driving with drowsiness is one of the primary causes in traffic mishaps [1]. According to experts, a driver who does not take a break when driving long distances is the one who is more prone to get drowsy [2]. There are lots of road accident happening in the world due to driver drowsiness and it even causes more road accident than drink-driving. Drowsiness is an abnormal feeling of being sleepy or feeling tired during the day [3]. It is simply defined as "a state of near-sleep due to exhaustion." by [4]. It affects someone's concentration, reaction time, productivity and more importantly safety in doing the normal day-to-day activities. It is said to be one of the contributing factors in road accidents globally [5]. Road accident is the fourth among the leading causes of death worldwide. Likewise, sleep-related vehicle accidents occupy the biggest portion in the road mishap and approximately 1.3 million individuals all over the world perish each year due to road misfortunes [6]. By the year 2020, road accidents are expected to increase to 5 million based on forecasting [7]. Based from the Philippine Statistics Authority (PSA), due to road related accidents there are about 34 Filipinos die every day [8]. It is an alarming issue in the Philippines that since 2006, deaths related to road accident is continuously increasing. Human error such as inattentiveness, tiredness, sleepiness, and a lot more has been the top reason for road mishap in the Philippines [9].

In today's world, technology almost changes everything with its constant advancement in medicine and health care, communication, agriculture, education, and transportation [10]. With the development in the field of computer technology, car safety has been an area of interest in research. Most of the accidents caused today by cars are mainly due to driver drowsiness. With this, there is no measuring tool that can scale drowsiness level but there are some signs including the eye movement, yawning, pulse rate, brain activity, and breathing rate which may tell whether a person is drowsy or not [11]. The study on measuring drowsiness level of the driver is categorized into three techniques: 1) Vehicle Behavior based with the use of mechanical and sensor 2) Biological Signal based that use sensor, and 3) Image Processing that involves computer vision that focuses on changes on facial feature which is one of the associated signs to drowsiness [12]. In fact, the existing solution that address drowsiness of the driver is categorized into two classifications – intrusive and non-intrusive systems. Intrusive system is the most accurate since it measures physiological signals but is said to be annoying on the part of the driver for it require sensors to be wear for an instance just like the Advance Safety Vehicle (ASV) developed by Toyota, Nissan, and Honda that uses wristband in monitoring the drowsiness based on the pulse rate [13]. On the other hand, non-intrusive system focus on facial feature changes under different lighting, face angles and expression [14][15] like the observance of eye closure in drowsiness detection for it is said to be the first and most important sign to look at the various table text styles are provided. The formatter will need to create these components, incorporating the applicable criteria that follow.

A. Background of the Study

The use of Image processing technique attains a highly precise detection of drowsiness as compare to other techniques. Over the past decade, many researchers have worked on developing a system that monitors drivers' drowsiness. Different parameters were considered in different studies like [15] focusing in the mouth yawning which consisted of 20 yawning images captured in videos using Support Vector Machine (SVM) as training sets and it acquired an accuracy performance of 81%. However, the study recommends to integrate more facial features for a more accurate detection while [16] developed a new solution by using different color spaces (RGB, YCbCr and HSV) to improve the effectiveness of face detection, yawning mouth can be identified by having a yawn component and eventually verified it to mouth location – resulting to an accuracy performance of 70% hence, the proposed model only detects frontal view images. In addition, [17] presents a new system concentrating on yawning analysis, comprising of 400x320 RGB size images and video formats with the aid of AdaBoost for face detection, Viola-Jones face region extraction, and Fuzzy c-means (FCM) for lips segmentation. Mouth activity is regularly observed only at every fifth frame – reaching an average of 92% accuracy, the researchers suggest to make a more accurate fatigue detection system. Aside from focusing on yawning, [18] a developed driver drowsiness detection was introduced using the Haar-cascade in tracking the eye. The combination HOG features and SVM Classifiers were also utilized in detecting the eye-blinks, with a threshold of 6.00 seconds and accounted an accuracy rate of 91.06%. However, the system only works accordingly under a normal lighting condition and a single feature. Additionally, [19] it mainly concentrates on detecting drowsiness anchored on eye closure and depended on the use of Haar-cascade and SVM; it achieved a rate of 92.45% with correct detection of drowsiness. Many researchers have worked on combining both elements of eye-blinking and yawning in monitoring the drivers' drowsiness, [20] and it utilized the Haar-cascade for facial features detection and various algorithms. The Contour algorithm was used to detect yawning with applied calculation on getting the smallest and largest y-coordinate values which then sought for the difference to get the height. Its greater values compared to a certain threshold served as an indication of yawning. The same concept is applied in the eye-blinking detection using Viola-Jones algorithm and it achieved an accuracy performance of 88.41% for eye-blink recognition and 83.66% for yawning. Moreover, [21] a drowsiness detection using Viola Jones Algorithm was developed, where it monitors the closing of the eyes and yawning on around 1000 positive and 5000 negative subject samples. Closing of the eyes served its primary condition and yawning of the mouth came as second condition. It approximately achieved 450ms in detection of drowsiness. The system detected multiple faces which increased the chances of false detection and the study took a long time training the datasets. Furthermore, [11] monitoring the eye-blink and yawning of the subject have been the focus of study by using AdaBoost Algorithm for face detection, Histogram of Oriented Gradients for facial features extraction, and SVM in classifying the eye-blinking and yawning – achieving an accuracy performance rate of 85.7% in detecting drowsiness. The limitation of the developed system is its low accuracy of detection if given multiple angles in terms of the driver's face to the camera.

The published studies cited provided an insight for this study to easily identify the knowledge gaps in the field of drowsiness detection. It served as both basis and inspiration of the proposed model in this study. Nevertheless, the previous researches took so much time in training datasets that contain different drowsiness activities; some papers recommend to increase accuracy rate of detection; and other model works on frontal view face only. Therefore, this study took into consideration the slight variations of the face angle by taking positive 45° to negative 45° of real-time videos to monitor the drivers' facial features – merging the closure of the eyes and yawn detection method to increase efficiency and intelligence of the decision in integrating the alarm system when the Eye Aspect Ratio goes below the threshold of 0.25 for 30 consecutive frames. A secondary alarm will also trigger when yawning indication exceeded a 0.60 threshold value for 30 consecutive frames.

B. Research Objectives

- To utilize the existing 300-W datasets composed of different styles and face angle images.
- To apply an API with Histogram of Oriented Gradients + Linear SVM method for face detection and classification, Random Forest for eye and mouth extraction, and Euclidean Distance for detection of yawning and eye blinking.
- To test the accuracy of detection in multiple disciplines.
- To design the prototype model that provides better accuracy results.

C. Conceptual Framework

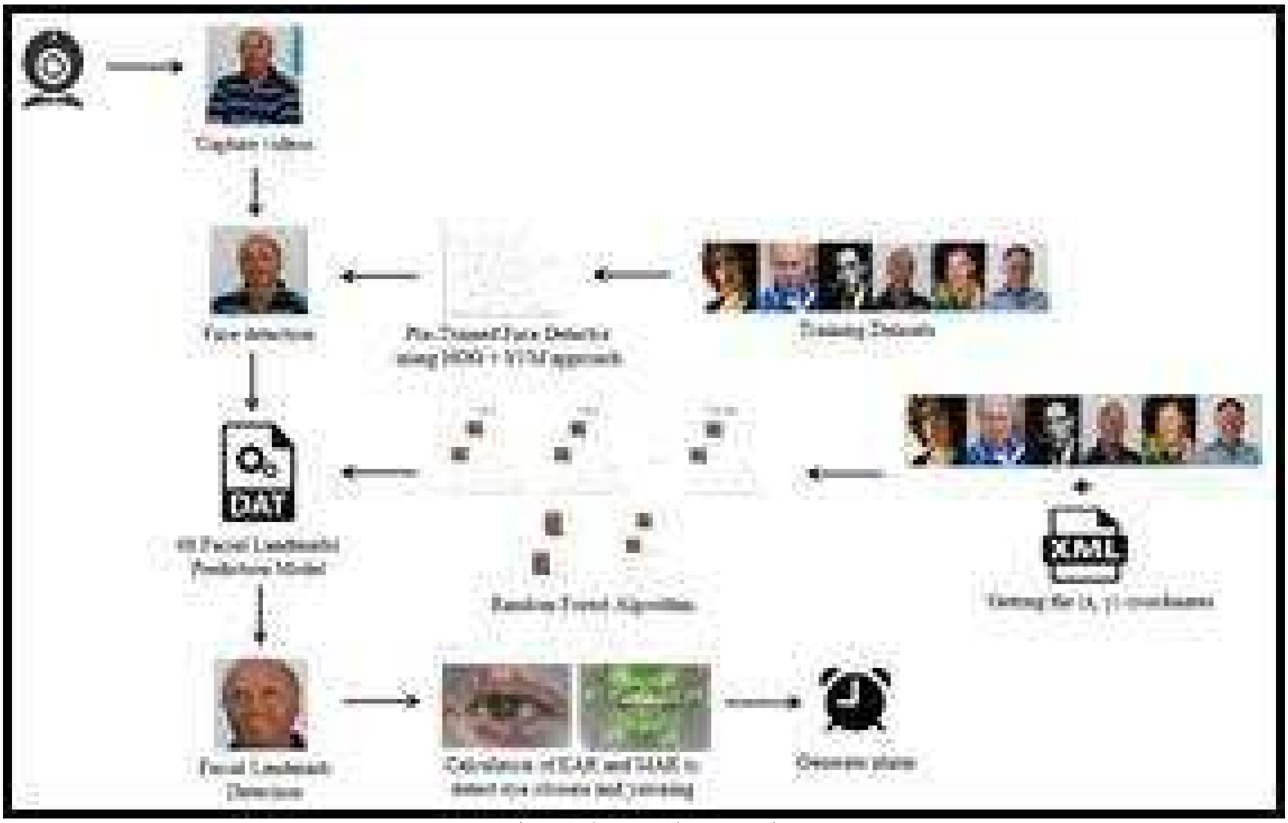

Figure 1. Conceptual Framework

The model captured real-time videos using an Oppo A3s– 1080p Camera attached to a laptop to detect the drivers' facial features. The face image was designed to be detected using an API Based Histogram of Oriented Gradients with both Linear SVM and Random Forest to identify the face landmarks. For the extraction of eye and mouth, the aspect ratio would be determined, the values 37 to 42 were assigned for the left eye, 43 to 48 for the right eye, and 49 to 68 for the mouth together with the basis of calculating the threshold. Thus, if the threshold turned to be less than 0.25 for eyes and greater than 0.75 for yawning detection in 30 consecutive frames, the prototype would provide an alarm sound and implied the detection of drowsiness

D. Theoretical Framework

Histogram of Oriented Gradient (HOG) is proven effective to be used in object detection, human detection, face detection, hand detection and the like. [22] [23]. It is usually being used for it is not very sensitive in light and small offsets. It also converts an image to grayscale and extracts multiple scale textures of face in different sizes. Moreover, a study of Rekha et al., HOG was also applied in detecting face. They calculated the HOG weight of the image to locate facial features. Their proposed model detected the face from +90° to -90° and worked even with occluded face in any orientation, low quality image, and skin color.

D1. Support Vector Machine: Support Vector Machine (SVM) is used in image processing, text classification and many other purposes. Its advantages include the accuracy, robustness, and best classification function in the assessing two classes of data while its disadvantages include the memory requirement, and computation complexity [25]. In a study conducted by Ojo, the researchers used SVM in classifying feature vectors that detected yawning and eye-blinking – illustrating good result which then, the researchers in this study considered The system's face detection used a pre-trained Histogram of Oriented Gradients (HOG) to extract the features and be inputted to the Linear SVM classifier using the iBUG 300-W face landmark dataset.

D2. Random Forest Algorithm: Random Forest (RF) is one of emerging techniques and it runs faster in training and testing phases compared with other classifiers [26].

Furthermore the higher number of trees and repetition entails a more accurate classifier [28][29]. This is implemented in this paper through a Shape Regression for Face Alignment.

II. METHODOLOGY

A. Face Detection (Pre-Image Processing)

Figure 2. (a) raw image (b) resized image (c) RGB to grayscale

The study used an API of HOG (Histogram of Oriented Gradients) face detector from i-Bug 300W dataset, composed of 300 outdoors and 300 indoor images with various poses and sizes. The images were cropped to 400x400 pixels then inputted to the API which were resized into 200x200 pixels. The images were also converted from RGB to grayscale for the calculation of HOG features as shown in Figure 2, see Wikipedia: https://en.wikipedia.org/wiki/Histogram_of_oriented_gradients

B. Training Stage

Figure 3. XML File of Landmark Points

Fig. 3 shows the 600 images from iBug 300-W datasets. The study labeled the images with 68 Facial Landmark Points – (x,y) coordinates using a web-based application, ImgLab. These were stored in the XML File.

Each of the images had their own respective 68 Facial Landmark.

Figure 4. Mean Shape

In order to get the mean shape, and the XML shape points, the average were acquired by dividing it by the number of Training images.

Shape Regression for Face Alignment:

$$S^t = S^{t-1} + R^t(I.S^{t-1}) \quad (1)$$

Given a facial image I and an initial1 face shape of S0, each repressor computed a shape increment of δS from the features which then updated the face shape in a cascaded manner. The *t*th weak repressor R^t updated the previous shape S^{t-1} to new S^t shape.

C. Landmark Annotation Processing Stage

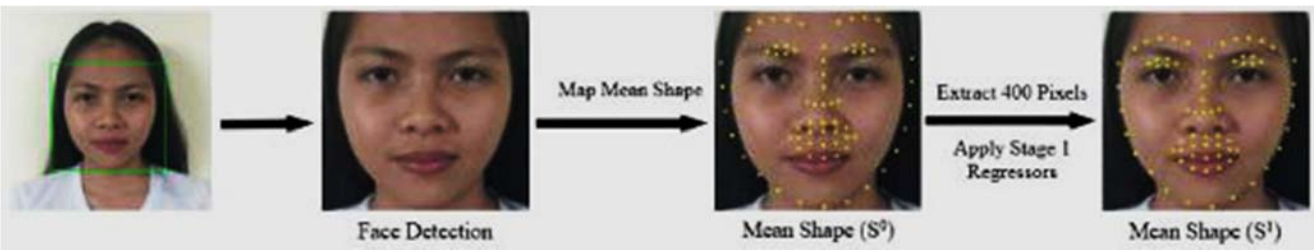

Figure 5. Initial Mean Shape Allocation

The study captured a live feed video to detect the face of the subject – localization such as the jaw, nose, lips, and eyes. Then, the mean shape was mapped based on the trained mean shape from the DAT file stored in the directory of the prototype.

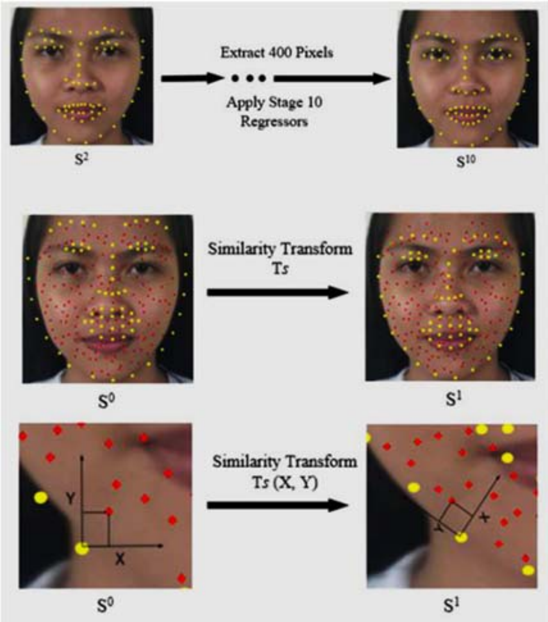

Figure 6. Similarity Transform

Once the S0 or the mean shape was already mapped in the image, the first stage used the Similarity Transform through a regression approach. There were 500 trees in the regression that were compared until such a nearly correct shape was found. The Similarity Transform worked by indexing a pixel (red dots) from the extracted pixels by its local coordinates (δx, δy) in accordance to its nearest landmark (yellow dots). For each repressor Rt, it randomly selected two different pixels, and located the nearest facial landmark. It then calculated the Similarity Transform by slightly adjusting the landmark points through multiplying Similarity Transform to X and Y coordinates of certain pixel intensities with the nearest landmark.

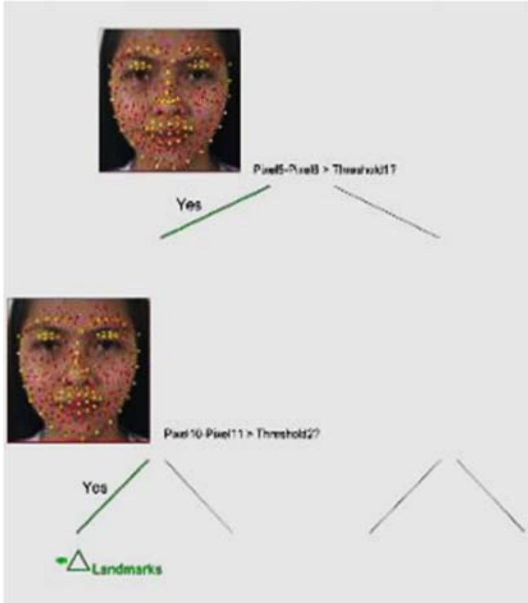

Figure 7. Regression

Fig 7 shows the regression localization stage of facial landmark points to get better results. There were 500 decision trees with 2 Nodes Split to slightly move the landmark points. The landmarks had a tendency of increasing down, left or right depending on the randomly selected threshold. If the given pixel value of Threshold1 was 0.00342, and classified as less than the value of the difference of Pixel1 and Pixel2 which was 0.00450, will be transfer to the left side of the decision tree until it reached the end node or the leaf. This process was applied from Stages 2 up until 10 Regressors. Weak regressor was more efficient because it prevented oscillation when placing the landmarks.

Figure 8. Delta Landmarks

Every leaf in the 500 trees, produced a Delta Landmark, which referred the dimension vector of pixels.

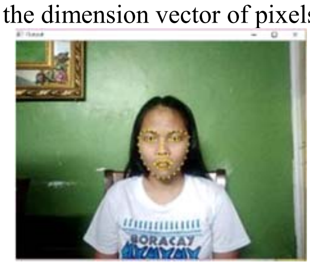

Figure 9. Desired Result of the Actual Landmark Annotation

It served as the new value of a certain landmark point. This was applied in each of 500 trees to acquire the Delta Landmark

Fig 9 shows the representation of what would be the desired results after the application of every regressors with the actual landmark annotation of the model

D. Mouth and Eye Landmark Extraction

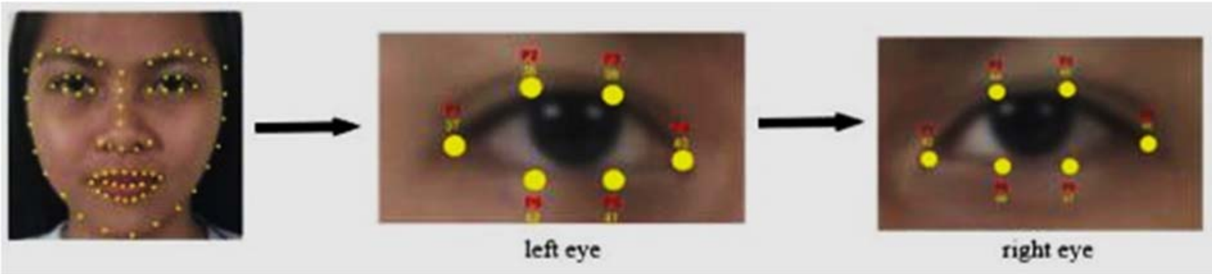

Figure 10. Eye Landmark Points

Fig 10 on the other hand, shows the landmark points from the resulted landmark annotation. To extract the eye landmark, it was addressed by using the labeled 68 Points, left eye points were 37 to 42 and the right had 43 to 48. The Eye Aspect Ratio or E.A.R. would be the basis to conclude whether the subject was closing its eyes or not using Euclidean Distance. If E.A.R. turned to be less than 0.25, it would be declared as closed.

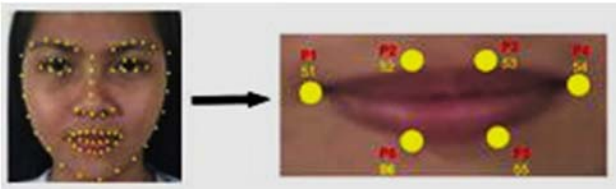

Figure 11. Mouth Landmark Points

Fig 11 shows the landmark points from the resulted landmark annotations. To extract the Mouth landmark, it used the labeled 68 points with mouth points of 51 to 56. The Mouth Aspect Ratio or M.A.R. served as the basis to conclude whether the subject was closing its eye with the aid of Euclidean Distance showed in Eq 2. If M.A.R. was greater than 0.75, it would be declared as a yawning mouth.

$$\frac{\|P2 - P6\| + \|P3 - P5\|}{2\|P1 - P4\|} \qquad (2)$$

Eq. 2 shows the equation of the Euclidean Distance algorithm that was applied in both the eyes and the mouth to get the aspect ratio

E. Prototype Model

The proposed system was developed using different tools. OpenCV was the software used by the researchers for computer vision and machine learning library. OpenCV is open source that has several applications. Python served as the programming platform in developing the prototype model because of its efficiency and compatibility with OpenCV. I-Bug 300-W Datasets was used for training the model – a recently collected dataset having 2x300 (300 for both indoor and outdoor) face images gathered in the wild. The images were downloaded from the web with a huge variant of uniqueness, expression, lighting conditions, postures, occlusions, and face sizes. In creating the allocation of the image coordinates (x and y), the researchers used ImgLab which is a web-based application, open source, and requires less memory. The collected allocations were stored in the XML file for trainings. Oppo A3S served as an improvised USB Web camera.

F. Metrics of Evaluation

$$Accuracy = \frac{TP + TN}{(TP + TN + FP + FN)} \; X\,100 \qquad (3)$$

In this study, drowsiness activities could be identified by eye closure, yawning, or both if performed simultaneously by the subject. True Positive (TP) condition was applicable when the model detected true drowsiness activity, True Negative (TN) was when non-drowsiness activity was correctly distinguished by the model, False Positive (FP) was when the system detects drowsiness activity that was supposedly none, and False Negative (FN) for drowsiness activity that was incorrectly detected.

For testing, there were two experiments conducted in the study, (1) camera was placed somehow under the front of the subject (O°) and (2) camera was positioned on the right-side of the user (45°). The researchers asked for 10 people to test the model consisting of 7 males and 3 females – with one (1) subject wearing eye-glasses. Each subject was requested to perform, 1) eye closure, 2) yawning, and 3) both. The actual testing was not done inside the vehicle for it was tested under normal lighting condition only. Oppo A3S served as the improvised USB camera.

In executing the project, there were four conditions that could be encountered.

TABLE I. DECISION MAKING

Condition	Eye Closure	Yawning	Message Displayed
Condition 1	No	No	None
Condition 2	Yes	No	Eye Closure Detected
Condition 3	No	Yes	Yawning Detected
Condition 4	Yes	Yes	Drowsiness Detected

III. RESULTS

A. Drowsiness Detection Accuracy

(a) Non-Drowsiness Activity (b) Eye Based Drowsiness

(c) Mouth-Based Drowsiness Activity (d) Eye and Mouth-Based Drowsiness

Figure 11. Screenshot of Non-Drowsiness and Drowsiness Detection in 0° Angle Camera Setup

These result illustrate that the model detected drowsiness for simultaneous yawning, and eye closure and thus, the installed alarm was triggered in order to give warning information labelled as yawning detected, drowsiness detected, and eye closure detected.

TABLE II. DROWSINESS DETECTION IN 0°

Type of Detection	Eye Closure	Yawning	Both
TP	10	8	7
TN	10	10	10
FP	0	0	1
FN	0	2	2
Accuracy	100%	90%	85%

Table II expounds the result of the system's detection in different drowsiness activities for the 10 subjects tested. Eye closure could be easily detected by the model, having a 100% accuracy rate. Yawning detection achieved a good result but had some false detection for the reason that some subjects have big mouth opening when yawning that exceeded too much for the facial landmark which challenged the extraction of the mouth points, the combined mouth-based and eye-based drowsiness activities – achieving an 85% rate of accuracy. The system couldn't accurately detect the yawning. For an overall performance, the model attained a 91.67% accuracy rate for 0° angle.

(a) Non-Drowsiness Activity (b) Eye Based Drowsiness Activity

(c) Mouth Based Drowsiness Activity (d) Eye and Mouth-Based Drowsiness Activity

Figure 12. Screenshot of Non-Drowsiness and Drowsiness Detection in 45° Angle Camera Setup

TABLE III. DROWSINESS DETECTION IN 45°

Metric	Eye Closure	Yawning	Both
TP	10	9	7
TN	10	10	10
FP	0	0	0
FN	0	1	3
Accuracy	100%	95%	85%

Table III shows the result of the detection under 45° camera angle. The developed model could easily detect the eye closure, reaching a 100% accuracy in performance while yawning detection marked a good performance as compare to the previous experiments done. However, the combined mouth-based and eye-based drowsiness activities achieved a low accuracy rate with 85% - mainly because there were instances that both eye closure and yawning were not performed simultaneously which then resulted to some false detection. For the model's overall performance, the model managed to attain a rate of 93.33% accuracy for 45° to -45° angles.

IV. CONLUSION

Based from the results, the eye closure consistently provided a 100% detection rate in both different camera angle setups in this study. However, the yawning and the combination of eye and mouth drowsiness activities had encountered limitations in terms of detection and recognition. Thus, for further enhancements, the study recommends to provide various computations for yawning and eye aspect ratio to be able to make a more efficient and flexible model in detecting drowsiness.

ACKNOWLEDGMENT

We wish to thank Dr. Lorena W. Rabago, Dr. Maryli Rosas, Prof. Maria Art Antonette Clarino, and Prof. Raquel Bermudez for helping us to improve the paper. Also, Ms. Jazmin Tan for reviewing the grammar and sentence structures of this manuscript. Likewise, the students of Saint Michael's College of Laguna for serving as subjects to test the prototype model.

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