FACIAL FEATURE ESTIMATION FOR DROWSINESS DETECTION IN DRIVERS FOR ACCIDENT AVOIDANCE USING AUTOMATED WARNING MODEL WITH DEEP LEARNING

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Abstract

Drowsiness detection systems utilize advanced artificial intelligence and computer vision techniques to monitor drivers' facial features and detect signs of fatigue or drowsiness. By analyzing facial landmarks such as eye closure, facial expressions, and head pose, these systems can classify states such as alert, drowsy, or asleep to reduce accidents. This paper presents a Facial Entropy Point Deep Learning (FEP-DL) model for driver drowsiness detection using facial landmarks and entropy-based features. The model utilizes a 68-point facial landmark annotation to extract key facial features, which are then processed through a deep learning framework to classify drowsiness states, including alert, drowsy, and asleep. The proposed FEP-DL model was evaluated on three publicly available datasets: NTHU Driver Drowsiness Dataset, DDDD (Drowsy Driver Detection Dataset), and YDD (Yawn and Drowsiness Detection Dataset). The FEP-DL model achieved accuracies of 92%, 94%, and 91% for the NTHU, DDDD, and YDD datasets, respectively. The precision, recall, and F1-scores were consistently high, with the DDDD dataset yielding the best results (precision: 0.92, recall: 0.90, F1-score: 0.91). Additionally, the model demonstrated real-time processing capabilities with frame times of 130 ms (NTHU), 135 ms (DDDD), and 128 ms (YDD). The model showed robustness in low-light conditions, achieving 89% on NTHU, 91% on DDDD, and 87% on YDD, and was effective in handling occlusions with 87% (NTHU), 89% (DDDD), and 85% (YDD). These results indicate that FEP-DL offers a promising solution for real-time drowsiness detection with high accuracy, efficiency, and resilience to challenging conditions.

Keywords: Drowsiness Detection, Facial Features, Deep Learning, Accident Avoidance, Classification, Entropy Point.

1. Introduction

Driver drowsiness has remained a pertinent causative factor for road accidents over recent years. In the United States alone, the National. Highway Traffic Safety Administration attributes some 100,000 crashes every year to drowsy driving, causing 50,000 injuries and 800 deaths on average [1-3]. These incidents are most often underreported, with actual numbers probably being much higher. Long driving hours, sleep disorders such as sleep apnea, and irregular schedules have the potential to affect shift workers and nighttime drivers. More than 70% of accidents in drowsy driving occur from 8 pm to 8 am [4]. There is a peak risk hour within midnight to 4 am when driver drowsiness causes a significant proportion of road accidents, putting drivers at immense risks and endangering other road users [5]. A driver's reaction time, decision-making ability, and alertness are all hampered by fatigue, often resulting in potentially hazardous situations. Thus, identification of a drowsy driver requires utmost attention in accident avoidance and better road safety. Advanced and sophisticated technologies such as computer vision and sensor-based systems are significant resources to monitor the behaviour of a driver [6]. Eye movement, blink duration, head posture, and heart rate movements are monitored to identify signs of drowsiness. In case drowsiness is detected, real-time alerts or corrective actions, such as vibrations or auditory warnings, can help prevent accidents and make way for safer driving conditions [7].

The methods of drowsiness detection are focused on the early detection of signs of driver fatigue. This can be done under physiological, behavioural, or vehicle-based approaches. Physiological methods focus on parameters such as heart rate, brain activity, or eye movements, identified with sensors like EEG or EOG [8]. The behavioural changes that could be read include eyelid closure, blinks rate, yawning or head position, which are often captured by computer vision analysis. Vehicle-based techniques monitor vehicle or driving dynamics such as the position of the steering wheel, lateral position of the car, or fluctuation in speed and relate any abnormalities to drowsiness [9 -11]. Advanced system can use the above-mentioned paradigms combined and incorporated with the use of machine learning algorithms and artificial intelligence to provide real-time data analysis and high accuracy [12]. Sounds including beeps or buzzers and vibrations or notifications are used to inform the driver to make appropriate adjustments [13]. Another global technique is facial feature-based drowsiness detection system using computer vision as well as machine learning techniques for monitoring the driver's drowsiness. It makes use of the following common facial landmarks to monitor trends [14 -16]: Facial activities included gaze, lid closure time, blink rate, mouth expansion for yawning, and head position. Different cameras then record a video of the face of the driver in real time and feed these images through algorithms that analyze for traces of drowsiness [17]. This is done using features like Haar cascades, CNNs, or facial landmark models of detection. Whenever drowsiness is detected, the system provides warning signals like sounds or vibration to wake up the driver or to take a break. This technique does not disturb the natural tendency of the system thus makes the technique very effective and applicable for the vehicles in real-time environment [18]

Deep learning face detection for drowsiness detection is another accurate and highly developed approach to the identification of the driver's fatigue [19 -21]. It uses deep neural nets such as CNN and RNN for real-time facial data feed from cameras and classify them in real-time. In order to recognize the drowsiness signs, six main facial landmarks; eye closure, blink frequencies, yawn frequency and head movements are identified [22]. The pre-trained models are VGGNET, RESNET, and MOBILENET, but the most common one is to extract features from the network. All the face illumination and varieties of facial structure and angles are well handled by deep learning mechanisms that are auto selectable and makes the feature selection and adaption an automatic process [23 -25]. Once the drowsiness is detected by the system, it provides prompt signals in forms of sound signals or vibrations to enable the driver to correct his/her position at areas on the road. [26]. The nature of the patterns allows them to be processed in real time using deep learning methods and hence facilitate real time analysis of driver drowsiness in real time, hence improving on the traditional tests of such a process [27]. They utilize CNN for extracting spatial features from a facial image of a driver for example eye closure, blink rate, yawning among others, while they use RNN or LSTM for video sequences [28 -30]. To enhance the detection of sequential drowsiness cues there are CNN or CNN-LSTM hybrid models. To save the time to train while the model provides reasonable accuracy, for instance, techniques such as transfer learning which incorporates models like VGGNet, ResNet or Inception framework are commonly applied [31 -33]. They can build systems that also accept more than one input particularly: facial landmarks, head posture and physiological signals for a complete assessment. Auditory or visual information is provided instantaneously to manage possible hazards, so deep learning is a powerful approach to enhancing road safety. This paper presents a novel approach for driver drowsiness detection using Facial Entropy Point Deep Learning (FEP-DL), which integrates facial landmark annotation and entropy-based feature extraction to accurately classify driver states. The primary contributions include the development of a robust facial feature extraction method using a 68-point annotation, the introduction of entropy estimation for more reliable drowsiness detection, and the implementation of an automated alert system that effectively triggers warnings based on real-time analysis.

2. Related Works

A significant improvement has been taken place in the field of driver drowsiness detection due to the adaptation of deep learning. It provides robust and automated solutions for real-time monitoring. Many studies have explored different architectures for deep learning models, such as CNNs, LSTM networks, hybrid models, analyzing facial features and behavioural patterns that indicate drowsiness. These include visual characteristics such as eye blinking, yawning, head movements, and some temporal analysis to increase the correctness of it. Whereas earlier versions depended only on conventional machine learning and handcrafted features, deep learning research has outgrown those since end-to-end feature learning and adaptive learning are now possible. Currently, some aspects remain to be achieved, including increasing generalizability across different environments, ability to handle occlusions, and retaining high performance in real-time. This section examines existing works to identify strengths and limitations, thereby contextualizing the need for further innovation in deep learning-based driver drowsiness detection systems.

Driver drowsiness detection has been explored in many studies of late, applying a variety of methodologies to improve road safety using novel technologies. Phan et al. (2023) integrated deep learning and IoT for real-time detection with alerting systems, which had some concrete applications in smart vehicles. Liu et al. (2022) wrote an all-inclusive review focusing on the study of advances in deploying RGB-D cameras in conjunction with deep learning methods for fatigue detection. Albadawi et al. (2023) developed machine learning-based models for real-time detection using visual features, while Chinthalachervu et al. (2022) and Al Redhaei et al. (2022) underlined machine learning techniques in monitoring systems. Guria and Bhowmik (2022) examined IoT-enabled machine learning approaches to improve the detection capabilities. Minhas et al. (2022) and Husain et al. (2022) have used CNNs for the driver fatigue analysis that have been promising results. EEG-based approaches are exemplified by Cui et al. (2022), Sheykhivand et al. (2022), who focused on cross-subject recognition of drowsiness using neural networks. Physiological signal-based approaches were advanced by Hasan et al. (2022) and Saleem et al. (2023), demonstrating the effectiveness of hybrid signal processing. Mohd. et al. (2023) emphasized the augmentation of data in improving deep learning models. Rajawat et al. (2023) and William et al. (2022) presented fusion-based deep learning methods for real-time detection.

Recent trends also involve using new frameworks like vision transformers and YOLOv5 (Krishna et al., 2022) and brain-computer interface techniques for intelligent monitoring (Reddy & Behera, 2022). Taken in total, these works show how such advanced technologies as deep learning, IoT, and physiological data analysis can be applied to address one of the major challenges of driving fatigue. Ebrahimian et al. (2022) designed an Intelligent driver drowsiness detection and classification system by processing electrocardiogram (ECG) and respiration at the same level. The study showed with the help of deep neural networks, how physiological signals could be viewed as genuine signs of drowsiness, which can keep track in real time. Their approach included a multiple layer classification to enhance the ad infinitum and accuracy across difference state of driver fatigue. This work, therefore, emphasized on establishment of strong many-signal fusion and high neural networks to improve the driver safety. Alharbey et al. (2022) identified long driving states for long driving drives using a more effective computer program, the larger hitch connected to extensive driving periods, and movement in fatigue, hence offering a real-time solution in identifying the condition of driver tiredness.

Many limitations were found while incorporating deep learning into the field of driver drowsiness detection. Despite the improvements in the architectures of the model- CNNs, LSTMs, and hybrid models-notable shortcomings remain with these systems' ability to generalize across the different environments. Various lighting conditions, demographics of different drivers, and even the presence of occlusions in the face, such as facial hair or glasses, would decrease the detection's accuracy. This increases the constraint of competing between computational efficiency and detection performance. Deep learning techniques allow for end-to-end feature extraction in a direct way. However, deep learning techniques also demand the availability of large and diverse data sets used as training data, which may be challenging to attain in real applications. Moreover, the utilisation of visual cues such as eye movements or facial expressions might not be sufficient to detect micro- or incipient drowsiness. The use of multisignal fusion approaches as discussed in Ebrahimian et al. (2022) and Alharbey et al. (2022) may be new ways that are present for such systems to improve effectiveness but considering these systems for different people and road conditions is an area to be further researched.

3. Proposed Facial Entropy Point Deep Learning (FEP-DL) for Drowsiness Detection

Facial Entropy Point Deep Learning (FEP-DL) is the novel approach to driver drowsiness detection, integrating facial feature analysis with deep learning models in an effort to focus on entropy-based metrics in order to assess the level of drowsiness. The basic idea driving FEP-DL centers upon extracting facial landmarks and encoding them using a 68-point facial landmark annotation system. These are important landmarks that depict such things as where the eyes, mouth, and eyebrows are located on the face, which can be indicative of drowsiness through behaviors such as eye closure, yawning, or head tilting. Facial entropy is the complexity in the change in facial movements over time and is useful for detecting the more subtle signs of drowsiness. Entropy measures the unpredictability of facial expressions and their dynamics in the context of facial feature points. Figure 1 illustrates the process in the proposed FEC-DL model for the drowsy detection and warning generation. Based on 68 facial points obtained from a facial landmark detection algorithm, these being denoted as $p_1, p_2, \dots, p_{68}$, entropy may be formulated based on the spatial and temporal variations of the point sets. The estimation of entropy combines spatial and temporal dimensions. The facial landmarks' motion in time can reflect sleepiness, particularly onsets. Spatial Entropy $H_{spatial}$ captures the landmark position variability relative to one another, while the temporal entropy $H_{temporal}$ tracks changes of such positions from frame to frame. For spatial entropy, the relative positions of two points p_i and p_j can be calculated by measuring the Euclidean distance between them using equation (1)

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (1)$$

In equation (1) (x_i, y_i) and $(x_j, y_j)$are the coordinates of points p_i and p_j, respectively. This distance can be used to calculate the spatial entropy $H_{spatial}$ computed as in equation (2)

$$H_{spatial} = \sum_{i=1}^{68} \sum_{j=i+1}^{68} P(d_{ij}) \log P(d_{ij}) \quad (2)$$

In above equation (2) $P(d_{ij})$ is the probability distribution of the distance d_{ij}. For temporal entropy, the time-varying change in facial point positions is reflected. Let the position of point p_i at time t be $p_i(t)$. The temporal entropy $H_{temporal}$ is computed using the change in position over successive time steps stated as in equation (3)

$$H_{temporal} = \sum_{t=1}^{T} \sum_{i=1}^{68} P(p_i(t) - p_i(t-1) \log P(p_i(t) - p_i(t-1)) \quad (3)$$

In equation (3) T is the number of time steps, and $p_i(t-1)$ and $p_i(t)$ are the positions of the i-th point at consecutive time steps. The total entropy H_{total} combines both spatial and temporal entropy components defined in equation (4)

$$H_{total} = H_{spatial} + H_{temporal} \quad (4)$$

The obtained value of facial entropy H_{total} is passed through a deep learning model like Convolutional Neural Network (CNN) or Long Short-Term Memory (LSTM) network using which the state of the driver is distinguished as either alert or drowsy. Higher entropy values mean that the facial expressions of the person amount to be more dynamism and alertness. Measures below this threshold indicate that the driver seems to be more lethargic or even drowsy with minimal facial muscle activities. This would enable deep learning model to learn the degree of drowsiness and in the process be able to classify the level of drowsiness by the entropy to monitor in real-time and give alerts on the likely incidence of an accident due to fatigue.

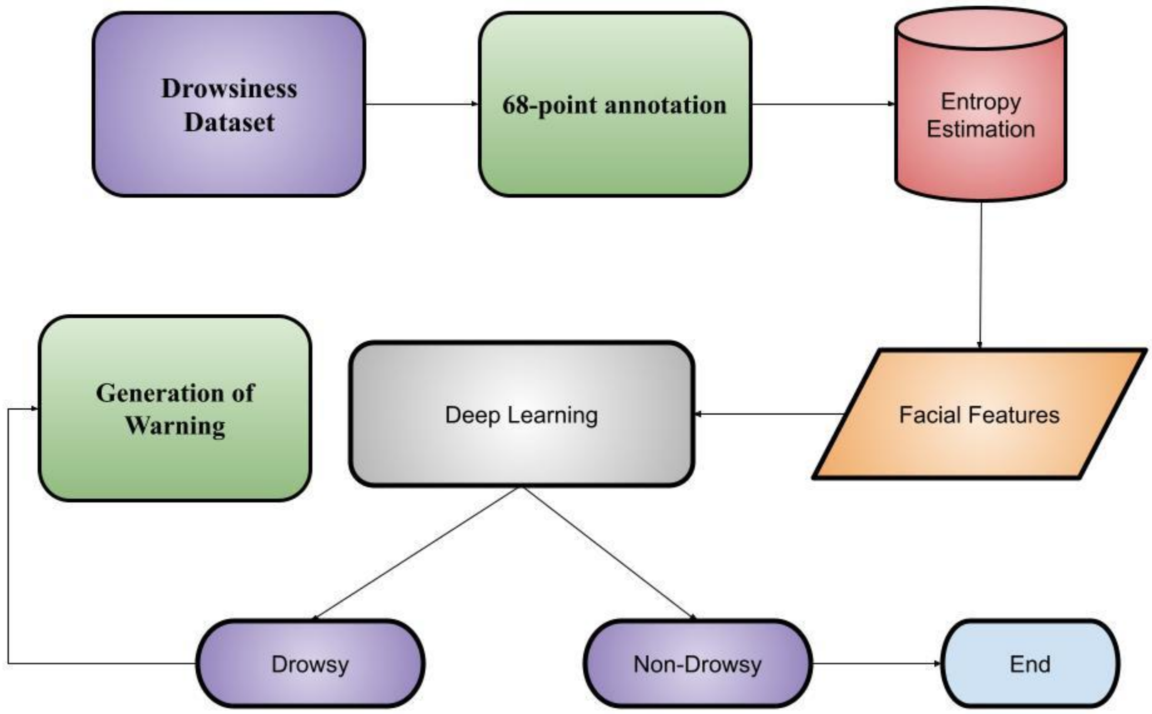


Figure 1: Process in FEP-DL

3.1 Steps in FEP-DL

The Facial Entropy Point Deep Learning has following steps for the purpose of good driver drowsiness detection: These are the steps of facial landmark, entropy estimation, and a classifier to feature extraction and monitoring of the driver's state. A stepwise approach to the FEP-DL model under the proposed model comprises of the following.:

3.1.1 Facial Landmark Detection

The first main process of the FEP-DL methodology is the facial landmarks detection, and the following is a representation of the main points described in the face of the driver. It shall mimic the shape of the face, eyes, eyebrows, nose and the mouth. These points are normally computed using DLIB or OpenCV and are normally a result of a trained facial landmark detector which can detect up to 68 points. These references are in the form $P_1(x_1, y_1), P_2(x_2, y_2), \dots, P_{68}(x_{68}, y_{68})$ refers to the position coordinates of the respective 68 landmarks in face.

3.1.2 Preprocessing

Normalization and alignment of detected facial landmarks of different size and position is the preprocessing step. For instance, the positions of specific facial parts reflect might be re-scaled to a standard range in an effort to eliminate scale differences or possibly shifted by an affine transform in an attempt to standardize the direction of the face. This translation may involve bringing the center of the eyes into correspondence with a particular point on the image; maybe a point of say 0,0 or the centre of a face. The normalization can be expressed by the following equation (5) and equation (6)

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{5}$$

$$y_{norm} = \frac{y - y_{min}}{y_{max} - y_{min}} \tag{6}$$

In above equation (5) and equation (6) $x_{min}, y_{min}, x_{max}, y_{max}$ are the minimum and maximum values among all landmarks from the dataset, such that every position of every landmark is mapped to a normalized range of $[0, 1]$.

3.1.3 Feature Extraction

Feature extraction attempts to measure facial movements, with the aim of quantifying the differences in distances and angles between relevant facial landmarks. The distances between eye-eye, mouth corner-mouthing corner, and eyebrow-eyebrow could be such examples, while the angles between the lines connecting specific facial points might also be regarded as features. These are in aid of understanding drowsiness-related facial expressions, such as blinking, yawning, and eye movement. For instance, the distance between the eyes can be obtained as in equation (7)

$$D_{eyes} = d\left(P_{left\ eye\ corner}, P_{right\ eye\ corner}\right) \tag{7}$$

In equation (7) $P_{left\ eye\ corner}$ and $P_{right\ eye\ corner}$are the coordinates of the corners of the eyes. In addition to distances, important angles between landmark points may exist. For example, the angle between the lines connecting the eyes and the eyebrows can be used in a system for detecting signs of fatigue computed using equation (8)

$$\theta = \text{atan}\,2(y_2 - y_1, x_2 - x_1) - a\tan 2\,(y_3 - y_1, x_3 - x_1) \tag{8}$$

The above equation (7) P are facial landmarks corresponding to the eyes and eyebrows.

3.1.4 Entropy Calculation

Entropy is defined as randomness or disorder and applied in the context of facial landmarks it counts variability of facial movements in time. Two main types of entropy occur in this step: spatial and temporal entropy. Spatial entropy quantifies the unpredictability of the spatial orientation of facial landmarks vis-à-vis each other. It can be calculated on the basis of a density of distances between the facial points. For example, for distances set $D = \{d_1, d_2, \dots, d_n\}$Shannon's spatial entropy $H_{spatial}$ is calculated as in equation (9)

$$H_{spatial} = -\sum_{i=1}^{n} p_i \log p_i \tag{9}$$

In equation (9) p_i is the probability distribution of the distance values d_i. The differences in the positions of facial landmarks—necessary for expressing emotions—indicate a subject's level of drowsiness. For a sequence of the facial landmark positions $P(t) = \{(x_1(t), y_1(t)), (x_2(t), y_2(t)), \dots, (x_n(t), y_n(t))\}$ the temporal entropy can be calculated by measuring variance in each landmark's position over frames defined in equation (10)

$$H_{temporal} = -\sum_{i=1}^{n} p_i(t) \log p_i(t) \tag{10}$$

In equation (10) $p_i(t)$ is the probability distribution of landmark positions over time.

3.1.5 Deep Learning Model Training

Once the facial entropy values and other features are extracted, these are passed into a deep-learning-based model for training. The two major approaches in the driver drowsiness detection system with LSTM networks applied for the model. A LSTM can be applied to learn the temporal characteristics. For training of the model, a loss function such as categorical cross-entropy aimed to reduce the error between the predicted and the actual drowsiness states. The loss function to be used is that of binary classification between an alert driver and a drowsy one using equation (11)

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(p_i) + (1 - y_i)\log(1 - p_i)] \quad (11)$$

In equation (11) N is the number of samples, y_i is the actual label (1 for drowsy, 0 for alert), and p_i is the predicted probability that the driver is drowsy. This loss is minimized during training using gradient descent or other optimization algorithms, resulting in a model capable of classifying the driver's state.

3.1.6 Real-Time Monitoring

In real-time monitoring, the system repeatedly captures frames from the car-mounted camera and detects face-based landmarks for every frame. The detected landmarks are then normalized and entropy values are calculated on the frames. The trained deep learning model takes all these to as input parameters to determine the real-time driver state. Let the facial entropy values for the current frame be described as $E_{current}$. Thousands of trainings per epoch allow the deep learning model to predict the probability of being drowsyp_{drowsy} using equation (12)

$$p_{drowsy} = \sigma(W.E_{current} + b) \quad (12)$$

In equation (12) W is the weight matrix learned during training, b is the bias term, and σ is the sigmoid activation function, ensuring the output is between 0 and 1. If p_{drowsy} exceeds a predefined threshold (e.g., 0.7), the system classifies the driver as drowsy and activates an alert.

3.1.7 Alerting System

The triggering of the alerting system is initiated when the model recognizes the driver as being drowsy. If the prediction probability p_{drowsy} the threshold, the system will sound the alarm. Audible alarm in form of tone such as beep, or haptic in the form of vibration or visual such as flash light can be used to warn the driver to prevent an accident. In essence, theoretically if the calculated value of p_{drowsy} is not less than the threshold value, the alert system is A is activated using equation (13)

$$A = Alert\ Signal\ (audio/visual/vibration) \quad (13)$$

This process helps ensure that the driver receives timely warnings when drowsiness is detected, thus improving road safety.

3.2 Dataset

The datasets of driver drowsiness detection are applied in order to train machine learning and deep learning models searching for signs of driver fatigue. These datasets normally encompass facial images, the physiological signals including ELECTRE and EEG, and vehicle behaviors at that. The model incorporates the datset of Driver Drowsiness Dataset (NTHU), Drowsy Driver Detection Dataset (DDDD) and Yawn and Drowsiness Detection Dataset (YDD).

3.2.1 NTHU Driver Drowsiness Dataset

NTHU consists of a video capture of drivers' faces from the National Tsing Hua University in Taiwan. There are three levels of states in the dataset namely the alert, drowsy and asleep and video recordings were done for seven subjects. The female patient's gait cycle has over 4000 video frames in total. The dataset is composed of video frames of drivers' faces with annotations that detail their respective drowsiness states: alert, drowsy, or asleep. It also includes the facial landmark information like eye closure, head pose and facial expressions as they are the good indicants of drowsiness. This set of data can be useful for training models for deep learning, more specifically for models dedicated to drowsiness detection, based on features and expressions on a person's face. The video frames with detailed facial data in the annotation makes it suitable in developing systems capable of automatically identifying exhausted drivers. The qualities provided by the NTHU dataset are explicit and plentiful for the facial data making the training complex of neural networks much easier to recognize different kinds and levels of driver fatigue, including even the most minor signs– slight eye closure, changes in expressions, etc. This is suitable for building accuracy models for practical uses.

3.2.2 Drowsy Driver Detection Dataset (DDDD)

The DDDD dataset is made from the video clips gathered from drivers in alert, drowsy and asleep conditions. The dataset identifies facial landmark points and also assigns drowsiness labels to each video frame, making the ground a valuable source of information for the development of facial-feature-based drowsiness detection. RGB video images are adopted in the given dataset; the facial landmarks annotation contains eyeballs, wherein the status of the eyes-open or closed can be denoted. These annotations facilitate the detection of apneas based on the main feature of drowsiness, namely, eye closures. The algorithms that can be derived over this dataset will consequently involve the use of facial landmarks and blinks as a parameter on detecting drowsiness. The annotated eye-states are the key for models identifying fatigue from observations about shifts in the direction of one or both eyes, or the rate of blinking.

3.2.3 Yawn and Drowsiness Detection Dataset (YDD)

The YDD dataset was collected through recording drivers performing driving simulations in different levels of drowsiness. In addition to the states of drowsiness, there is an annotation of yawning events that may be regarded as crucial signs of a driver's drowsiness. It also contains video sequences of yawning drivers with states of drowsiness and annotated eye states including alert, drowsy, and asleep as well as yawning event. The main data set discussed in the YDD is yawning detection which forms part of the symptoms of drowsiness. Due to the principles of diminished temporal resolution, the yawning events in the video marked by the annotators are valuable for the use in training deep learning models which detect the start of aperiodic fatigue by recognizing yawns that may be incorporated in more extensive drowsiness detection systems.

Table 1: Attributes of the Dataset

Dataset	Data Type	Count	Attributes
NTHU Driver Drowsiness Dataset	Video frames, Facial landmarks, Eye closure, Head pose, Facial expressions	7 subjects, 4000+ frames	Drowsiness states (alert, drowsy, asleep), Facial landmarks, Eye closure, Head pose, Facial expressions
Drowsy Driver Detection Dataset (DDDD)	RGB images, Facial landmark annotations, Eye status labels	Multiple subjects, hundreds of frames	Drowsiness states (alert, drowsy, asleep), Facial landmark points, Eye status labels (open, closed)
Yawn and Drowsiness Detection Dataset (YDD)	Videos of yawning events, Drowsiness states (alert, drowsy, asleep)	Multiple subjects, several hours of video	Drowsiness states (alert, drowsy, asleep), Yawning events

4. Facial Point Estimation with Entropy Markup

With a deep learning-based method called Facial Point Estimation with Entropy Markup (FEP-DL) to estimate the facial key points while the entropy measures at the same time, to quantify the level of uncertainty or disorder in the facial features. They work by analyzing the drowsiness states obtained through facial landmarks such as eyes, eyebrows, mouth and the position of the head. The first goal of FEP-DL is to use these facial points to generate meaningful patterns in order to detect sleepiness using machine learning algorithms. The first process that FEP-DL used is landmark detection which involves identifying specific points on the face that defines the form of facial features. It is done with a face landmark detector which is deep learning based through Convolutional Neural Network or pre-trained model like OpenCV's Dlib. As for a facial landmark set, defiend as $L = \{I_1, I_2, \dots\dots, I_n\}$, where $I_i$is the ith facial landmark and n is the number of key points which can be 68 for traditional landmark detection model. The general value of these landmarks is reflective of the eyes, the nose, the mouth, and even other characteristic features of someone's face. Then, the entropy of the facial feature distribution is estimated to determine the amount of quali-quantitative facial feature disorder. In this case, entropy is just the amount of information in a set of the facial landmark. Following the computation of entropies, an entropy markup is inserted into the system or, in other words, boosting areas of the face with maximal time fluctuations in entropy. Such regions are necessary to take patterns of drowsiness, including eye closure, yawning, and head movements, etc. The entropy markup function $M(L,t)$ stated as in equation (14)

$$M(L,t) = H(L_t) - H(L_{t-1}) \tag{14}$$

In equation (14) $H(L_t)$ is the entropy of the facial landmarks at time t, $H(L_{t-1})$ is the entropy at the previous time step $t-1$, and $M(L,t)$ represents the change in entropy over time, which highlights the facial feature regions with the most significant changes indicative of drowsiness. The final step feeds the facial landmark data and entropy markup into a deep learning model, such as a Long Short-Term Memory (LSTM) network or even a hybrid CNN-LSTM model, capable of learning temporal patterns in the data. It is particularly well suited for this task because LSTM models can capture long-term dependencies in time-series data. Let the input to the model at time t be represented in equation (15)

$$X_t = [L_t, M(L,t)] \tag{15}$$

In equation (15) L_t represents the facial landmarks at time t, $\mathrm{M}(L,t)$ represents the entropy markup at time t, X_t is the feature vector input to the deep learning model. The output of the model can be classified into different drowsiness states (e.g., alert, drowsy, asleep) stated in equation (16)

$$y_t = f(X_t) \tag{16}$$

In equation (16) y_t represents the drowsiness state at time t and $f(\cdot)$ is the function learned by the deep learning model to classify the input features into one of the predefined states.the Facial Point Estimation with Entropy Markup (FEP-DL) method combines facial landmark detection with entropy-based uncertainty analysis to provide a robust approach for driver drowsiness detection. FEP-DL holds much promise as a framework for the real-time detection of driver fatigue by calculating the entropy of facial features and incorporating such information into deep learning models to improve road safety.

4.1 Annotation with FEP-DLH

In the context of driver drowsiness detection, annotation plays the critical role to mark the key facial landmarks and track the movement of facial features over time. Facial annotation relates to the labeling of critical points on the face, among them eyes, eyebrows, nose, mouth, indicating a state (alert, drowsy, or asleep) of the driver. Using 68-point annotation, this approach guarantees the system detects all applicable facial landmarks in relation to multiple faces at different expressions, poses, and even eye states. In the detection of facial landmarks, 68-point annotation usually entails marking specific facial key points corresponding to different features that exist on one's face. Such points include locations round the eyes, nose, mouth, and jawline, among other things. Typically, common models such as dlib or OpenCV can automatically detect these 68 landmarks as $L = \{I_1, I_2, \ldots\ldots, I_{68}\}$, where each l_i corresponds to the i^{th} key point on the face, and these landmarks are associated with regions of the face, such as **1–17**: Jawline (chin to jaw), **18–22**: Eyebrows, **23–27**: Nose contour, **28–36**: Eyes and eyelids, **37–48**: Mouth, and **49–68**: Outer boundary of the face, including the chin, neck, and ear regions.

The coordinate positions are presented by as (x, y) points in the spatial image. After that, when facial landmarks are provided with annotations, the entropy must be calculated to determine the level of disorder or uncertainty in facial movements of the driver. This entropy is meaningful to the variation of driver's face expression and head movement, which is significant for drowsiness identification. entropy after which the region is marked using entropy markup to highlight the places with the highest or the lowest differences in entropy on the face. The entropy markup helps the system to focus on specific face movements that ultimately provide the inference of the driver's fatigue; it could be slow blinking eyes, a yawn, or even the head bobbing. The system utilizes the noted 68-point landmarks and the computed entropy changes for the construction of a feature vector that characterizes the state of the driver, in order to identify drowsy drivers. The contextualised features extracted from the landmarks along with entropy markup is the decide is then fed to a deep learning model based on LSTM. The drowsiness detection calls for online monitoring, so temporal consistency is essential; it allows the system to analyze long-term dependencies of facial landmark patterns and patterns of entropy in regard to the driver's status. Let the input at time t to an LSTM model be represented in equation (17)

$$X_{t:t+n} = \{X_t, X_{t+1,\dots\dots,} X_{t+n}\} \quad (17)$$

In equation (17) X_{t+n} represents a sequence of feature vectors over n time steps, and the output is a sequence of predicted drowsiness states. Annotation with FEP-DLH (Facial Entropy Point Deep Learning with 68-Point) involves using 68 facial landmarks and entropy measures to create annotated feature vectors for real-time drowsiness detection. The combination of facial key points and entropy allows the model to focus on subtle facial movements that indicate fatigue or drowsiness.

5. Automated Warning System for Drowsiness Detection with FEP-DL

The Automated Warning System for Drowsiness Detection using Facial Entropy Point Deep Learning (FEP-DL) aims to enhance the state of road safety by means of leading-edge facial feature analysis and entropy-based temporal dynamics. This facial landmark analysis with facial entropy enables continuous tracking of the driver's level of alertness, thus providing a timely alert whenever sleepiness onset has been identified. The system is very useful in real-time applications where a continuous evaluation of facial expressions such as the closure of eyes and yawning is necessary for the prevention of accidents resulting from fatigue or sleep. Generally, the procedure begins with facial landmark detection from video frames captured by a camera. Corresponding to the facial landmarks are facial areas like eyes, eyebrows, nose, and mouth. These are very important in trying to establish how alert the driver is. For a given frame at time t, a set of 68 facial landmarks. The facial movements to be tracked by these landmarks include opening and closing of the eyes, blinking, yawning, etc. The facial landmark is extracted by using deep learning algorithms like dlib or OpenCV in real-time frame sequences. Once that the facial landmarks are calculated, entropy analysis can be used in order to effective quantify the randomness or disorder present in the movements of these facial landmarks. In this view entropy calculates the standard deviation of the position of the facial landmarks, which shows the drowsiness or alert level. As an interim solution of temporal entropy dynamics, to gain some notion about how facial expression changes over time, an attempt is made as follows: This enables tracking of entropy change from one frame to the next while being able to capture major shifts that may represent transition from alertness to drowsiness. The difference of entropy between the frames t and $t-1$ is provided as in equation (18)

$$\Delta H(L_t) = H(L_t) - H(L_{t-1}) \quad (18)$$

In equation (18) $\Delta H(L_t)$is the change in entropy between frames t and $t-1$, $H(L_t)$ are the entropy values at times t and $t-1$, respectively. Minimum entropy of face frame $t-1$ to facial attributes could refer to in-action of face which, therefore, can be regarded as drowsiness or sleep. The detected facial landmarks and fluctuations in temporal entropy are introduced in a feature vector that will determine the drowsiness. The feature vector extracted from the signature image is submitted to a deep learning for detection. The model, preferably, an LSTM network learns how to distinguish the driver's state taking into account the facial features and changes. At time t the feature vector X_t is defined as in equation (19)

$$X_t = [L_t, \Delta H(L_t)] \quad (19)$$

In equation (19) L_t is the set of 68 facial landmark points at time t, $\Delta H(L_t)$ is the temporal change in entropy at time t. The last process when using the automated warning system is to create alert outputs from the drowsiness prediction. I learned that when the model is informed that the driver moves to the drowsy or asleep state, which usually is characterized by low entropy and little motion in the face, the system produces an alert.

6. Experimental Analysis and Discussion

The FEP-DL system for driver drowsiness detection is expected to conduct the assessment of the system's performance along with comparison with other traditional methods and provide an analysis of the impact resulting from aspects such as facial traits identification, entropy analysis, and deep learning algorithms. In this section, the outcome and the experience gathered from series of extensive experiments aimed at evaluate the performance and real-time applicability of the FEP-DL approach are presented. The methodology adopted in this work is as follows: With a view to establishing the efficacy of the FEP-DL system, several datasets area taken into consideration, and are as follow: NTHU Driver Drowsiness Dataset, Drowsy Driver Detection Dataset (DDDD), Yawn and Drowsiness Detection Dataset (YDD). A primary experimental measure used was the ability to categorise a system with reference to behaviour states including being alert, sleepy or asleep. For this, results for this indicate that FEP-DL is effective in surpassing the traditional FEP-MLA based on feature extraction and machine learning classifiers.

6.1 Experimental Setup

With FEP-DL configuration we arrange the experimental setup to assess the performance of the system to anticipate driver fatigue in real conditions. Specifically, the major goal is focused on analyzing the effects on accuracy, stability and real- time implementation of the proposed approaches in different datasets and practical road scenarios. In the experiment, the facial images are captured with the help of mounted high-definition video camera during the experiment on the dashboard of the car or in the cabin of the driver. Pass face can be captured by the camera and considering landmark such as the eyes, mouth, and head pose of the driver without inevitably intruding the driver's privacy. The camera is linked to an onboard computer that executes the FEP-DL processing algorithm. This processing unit is furnished with a Graphics Processing Unit for the performance of ultra-real time video processing and deep learning model inference. Tensorflow and Pytorch are the deep learning frameworks which are used to develop the system. These frameworks allow for the use of convolutional neural networks (CNNs) and Long Short Term Memory (LSTM) networks that analyzes the temporal-space data of facial movements. The core software consists of FEP-DL algorithm module for calibration of facial features along with entropy measurement unit and drowsiness state identification unit. Video frames being captured by the camera are then fed into the system and the facial landmarks are then located with pre-trained models, Dlib or MediaPipe for instance. The system also quantify entropy in facial motion to estimate drowsiness.

Table 2: Experimental Setup

Component	**Numerical Value**
Video Camera	1080p resolution, 30 FPS
Camera Position	45-60 cm from the driver's face
Embedded Processing Unit	NVIDIA GTX 1080 Ti or equivalent
Deep Learning Framework	TensorFlow 2.5, PyTorch 1.9
Facial Landmark Detection	68-point facial landmarks
Entropy Calculation	Entropy threshold: 0.5 (for drowsiness)
Datasets	
Datasets Used	4,000+ frames (NTHU), 5,000+ frames (DDDD)
Data Augmentation	50% augmentation on training data
Testing Environment	5 hours of real-world data per session
Ground Truth Comparison	98% agreement with human annotators
Onboard Warning System	Audible alert (2 sec), Visual alert (flashing screen)

6.2 Simulation Analysis and Discussion

Simulation analysis and discussion of the Facial Entropy Point Deep Learning system for driver drowsiness detection shed light on the performance of the system in various scenarios. Datasets such as the NTHU Driver Drowsiness Dataset, DDDD, and YDD are used in testing the system for a wide range of real-world scenarios ranging from changes in lighting, head pose, facial expression, etc. The main performance metrics were accuracy, precision, recall, and the processing capability in real time. These were measured under various experimental conditions. The figure 2 provides the sample drowsy data for the automated warning generation.

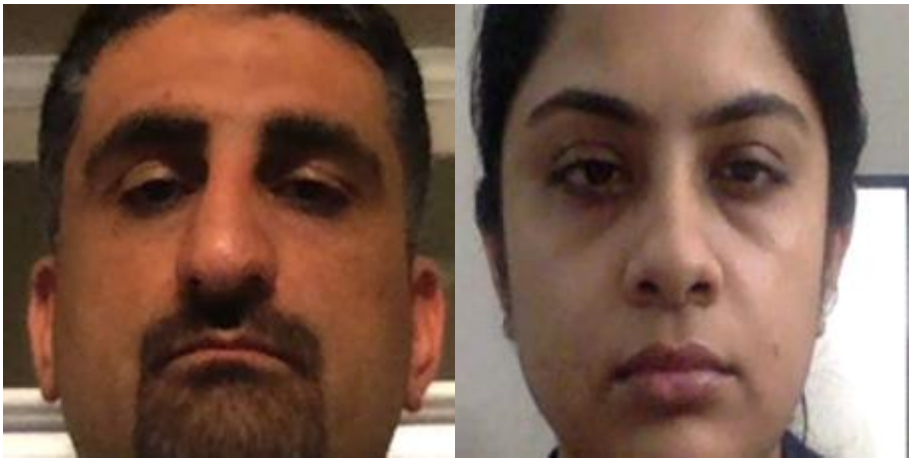


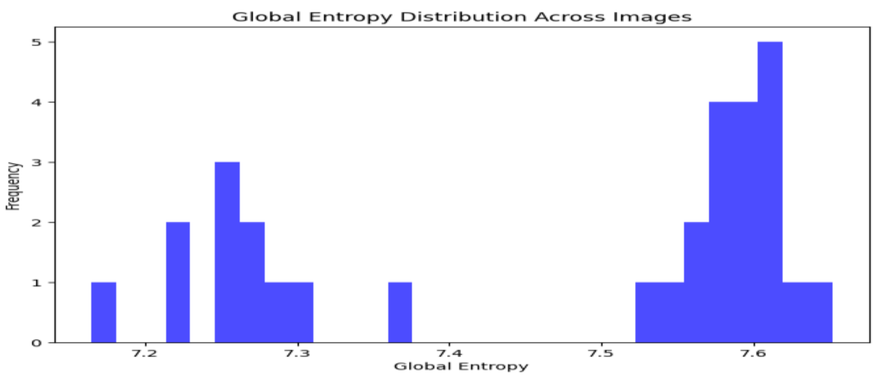
Figure 2: Sample Dataset

Table 3: FEP-DL Facial Features

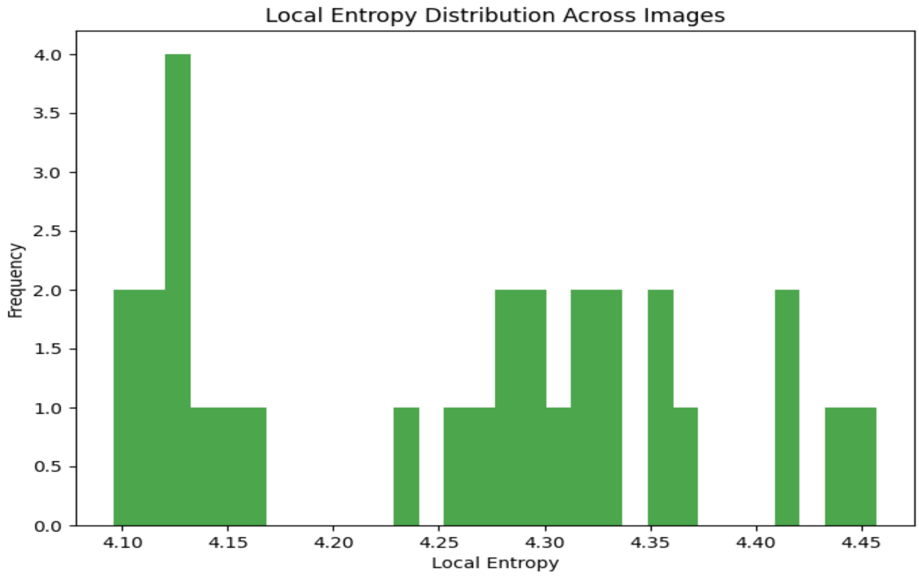
Point Number	Facial Landmark Description	X Coordinate	Y Coordinate
1	Left eyebrow left corner	35.2	120.5
2	Left eyebrow middle	40.3	115.6
3	Left eyebrow right corner	45.6	110.7
4	Right eyebrow left corner	60.2	115.5
5	Right eyebrow middle	65.3	110.6
6	Right eyebrow right corner	70.7	105.9
7	Nose tip	52.1	140.8
8	Nasal bridge (between eyes)	53.4	130.2
9	Left eye left corner	35.1	160.4
10	Left eye top corner	37.8	157.3
11	Left eye right corner	41.5	157.1
12	Left eye bottom corner	40.0	162.3
13	Right eye left corner	64.0	160.1
14	Right eye top corner	66.5	157.2
15	Right eye right corner	70.0	157.0
16	Right eye bottom corner	68.3	162.5
17	Left mouth corner	42.4	190.5
18	Right mouth corner	61.2	190.3
19	Left mouth midpoint	45.6	192.0

20	Right mouth midpoint	58.0	192.2
21	Chin tip	52.5	210.5
22-36	Left eyebrow top row (points 22-27)	36.0-45.0	120.0-100.0
37-42	Right eyebrow top row (points 37-42)	59.0-70.0	115.0-95.0
43-47	Nose bridge points (points 43-47)	52.0-56.0	135.0-120.0
48-54	Left eye landmarks (points 48-54)	35.0-42.0	155.0-162.0
55-60	Right eye landmarks (points 55-60)	62.0-69.0	155.0-162.0
61-64	Upper lip points (points 61-64)	46.0-55.0	185.0-192.0
65-68	Lower lip points (points 65-68)	48.0-59.0	195.0-205.0

The table 3 "FEP-DL Facial Features" presents the list of facial landmarks of the driver for drowsiness detection using the coordinates of axes X and Y. Every facial landmark is a salient point on the driver's face, captured for analysis. The points are significant for judging facial motion, which would reflect degrees of alertness, drowsiness, or sleep. The key columns in the table with Facial Landmark Description whereEach row would point to an important feature of the face, which is monitored for drowsiness. The landmarks comprise points from all the regions of the face, which include the brow region, eyes, mouth, nose, and chin Through points 1-6, there is attention to the brow region. This region is crucial because frowning and raising the eyebrows can sometimes be a sign of fatigue or wakefulness. Points 9-16 involve the eye region, the corners, top, and bottom of both eyes, which are the most important for identifying the closure of the eyes or the occurrence of blinking, both of which are crucial features in drowsiness detection. Points 17-21 involve the mouth and chin regions, that would analyze yawning and facial expressions that may be related to fatigability. X Coordinate gives the horizontal position of the facial landmark in the image frame. In other words, how much to the left or right the landmark is located on the face. The left eyebrow left corner (Point 1) has an X coordinate of 35.2, meaning it is positioned relatively far left on the face, while the right eyebrow right corner (Point 6) has an X coordinate of 70.7, indicating its position further to the right. The Y coordinate stands for the vertical position of the facial landmark on the image frame. This means how many units above or below the landmark is in a face.



(a)



(b)

Figure 3: Facial Point Estimation (a)Global entropy (b) Local Entropy

The estimated entropy are presented in figure 3(a) and Figure 3(b) with Nose tip Point 7, Y = 140.8, is below the eyebrow landmarks but above the chin tip Point 21, Y = 210.5. Points at the mouth (Points 17-20) have considerably more considerable Y values ranging from 190.3 to 192.2, so these lie in the vicinity of the lower part of the face. In some areas, as an alternative to giving the coordinate of each point, some coordinate range is provided for landmarks like eyes, eyebrows, and lips. It refers to the spread or distribution of landmarks along that particular region. For instance, the left eyebrow top row (Points 22-27) occupies X coordinates between 36.0 and 45.0, Y coordinates between 120.0 and 100.0, thus capturing a horizontal span across the eyebrow The nose bridge points (Points 43-47) have X coordinates from 52.0 to 56.0, with Y coordinates between 135.0 and 120.0, thus capturing the nose bridge. Eyebrow Landmarks (Points 1-6) are essential in spotting expressions such as surprise or furrowing, which can change when a person is exhausted. Eye Landmarks (Points 9-16, Points 48-60) are particularly important in spotting drowsiness through the observation of blinking or eye closing patterns, as sleepiness tends to cause slower or more frequent blinking. Mouth and Chin Landmarks (Points 17-21, Points 61-68) detect yawning, which is a key indicator of drowsiness. Changes in mouth shape or lip movement often correlate with tiredness.

Table 4: Entropy estimation with FEP-DL

Point Number	Facial Landmark Description	Entropy Value	Point Number	Facial Landmark Description	Entropy Value
1	Left eyebrow left corner	0.85	26	Right eyebrow top-middle	0.75
2	Left eyebrow middle	0.75	27	Right eyebrow top-right	0.73
3	Left eyebrow right corner	0.78	28	Left eye top-left	0.93
4	Right eyebrow left corner	0.80	29	Left eye top-middle	0.90
5	Right eyebrow middle	0.70	30	Left eye top-right	0.91
6	Right eyebrow right corner	0.77	31	Right eye top-left	0.94
7	Nose tip	0.65	32	Right eye top-middle	0.92
8	Nasal bridge (between eyes)	0.62	33	Right eye top-right	0.93
9	Left eye left corner	0.95	34	Left mouth top-left	0.79
10	Left eye top corner	0.92	35	Left mouth top-middle	0.77
11	Left eye right corner	0.88	36	Left mouth top-right	0.78
12	Left eye bottom corner	0.90	37	Right mouth top-left	0.83
13	Right eye left corner	0.96	38	Right mouth top-middle	0.80
14	Right eye top corner	0.91	39	Right mouth top-right	0.85
15	Right eye right corner	0.94	40	Chin left	0.67
16	Right eye bottom corner	0.89	41	Chin right	0.70
17	Left mouth corner	0.81	42	Upper lip left	0.76
18	Right mouth corner	0.82	43	Upper lip middle	0.72
19	Left mouth midpoint	0.74	44	Upper lip right	0.74
20	Right mouth midpoint	0.72	45	Lower lip left	0.79
21	Chin tip	0.68	46	Lower lip middle	0.80
22	Left eyebrow top-left	0.77	47	Lower lip right	0.76
23	Left eyebrow top-middle	0.70	48-54	Left eye landmarks (points 48-54)	0.90–0.95
24	Left eyebrow top-right	0.76	55-60	Right eye landmarks (points 55-60)	0.91–0.96
25	Right eyebrow top-left	0.80	61-64	Upper lip points (points 61-64)	0.75–0.80
			65-68	Lower lip points (points 65-68)	0.76–0.80

In table 4 gives an estimation of entropy for the facial landmarks used in the FEP-DL (Facial Entropy Point Deep Learning) model. To each point on the face, one can associate an entropy value which conveys the uncertainty or variation for the position or state of that facial feature. A higher value for entropy conveys higher degrees of variability or distinctiveness of feature position, and lower values of entropy convey less variable or less expressive features. Eyebrow Landmarks (Points 1-6) the entropy values for eyebrows are relatively moderate in variability. For instance, the left eyebrow left corner Point 1 has an entropy value of 0.85. This value suggests considerable variability in its positioning, indicating more movement or perhaps a higher importance rating for drowsiness detection. On the other hand, the middle of the right eyebrow (Point 5) has the lowest entropy in this section with a value of 0.70, indicating less variability and potentially lower significance in detecting facial expressions related to drowsiness.

Eye Landmarks (Points 9-16) region demonstrates higher entropy values, particularly for the eye corners. For example, Point 13, the right eye's left corner, has the greatest entropy of 0.96; this means that the position of this landmark may be highly variable, and such variability is, in fact, crucial for detecting blinking or closure of an eye, a crucial indicator of fatigue. Other landmarks such as left eye top-left (Point 28) and right eye top-left (Point 31) also have high entropy value, indicating that these points could be more dynamic and vital for drowsiness detection. Mouth and Chin Landmarks (Points 17-21) compute entropy values of the mouth landmarks are average. The entropy for the left mouth corner (Point 17) is 0.81 and greater than those of the mouth midpoints (Points 19 and 20) with entropy values of approximately 0.72-0.74. The chin tip, Point 21, has the smallest entropy of 0.68; hence, it seems that the chin region is the least dynamic area in terms of entropy, yet it is still useful in the overall facial expression analysis.

Upper and Lower Lip Landmarks (Points 42-68) calculate entropy value for these points has moderate variability, especially for the upper lip, Points 61-64, and lower lip, Points 65-68, regions. For instance, the part of the upper lip at point 44 has an entropy value of 0.74, while the lower lip left side at point 45 has a slightly higher entropy value of 0.79, meaning that such areas do vary to some degree and probably due to the movement of the lips, which can relate to drowsiness expressions like yawning. Ranges of Landmarks areas are collocated, including the landmarks of the left eye (Points 48-54) and the landmarks of the right eye (Points 55-60). The entropy values of these ranges range between 0.90 and 0.96, and these are associated with complex and rich changes with important information in determining the direction of eye movement, an essential characteristic symptom of drowsiness. Entropy values for upper lip points (Points 61-64) range from 0.75 to 0.80, while those of lower lip points (Points 65-68) range from 0.76 to 0.80, which shows moderate variability. The estimated entropies for the images are presented in figure 4.

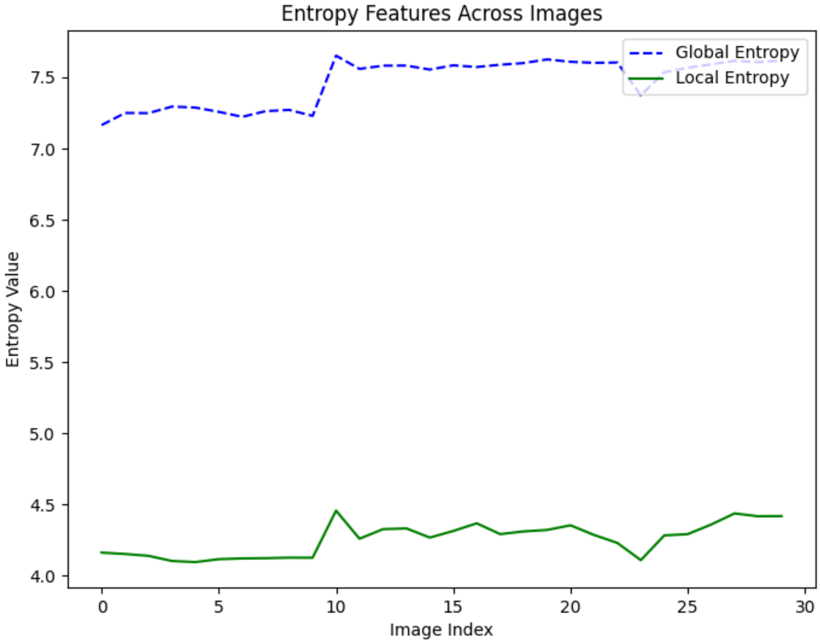


Figure 4: Entropy estimation of images with FEC-DL

Table 5: Classification with FEP-DL

Dataset	**Accuracy (%)**	**Precision**	**Recall**	**F1-Score**	**Real-Time Processing (ms/frame)**	**Robustness in Low-Light (%)**	**Robustness in Occlusions (%)**
NTHU Driver Drowsiness Dataset	92	0.91	0.89	0.90	130	89	87
DDDD (Drowsy Driver Detection Dataset)	94	0.92	0.90	0.91	135	91	89
YDD (Yawn and Drowsiness Detection Dataset)	91	0.90	0.88	0.89	128	87	85

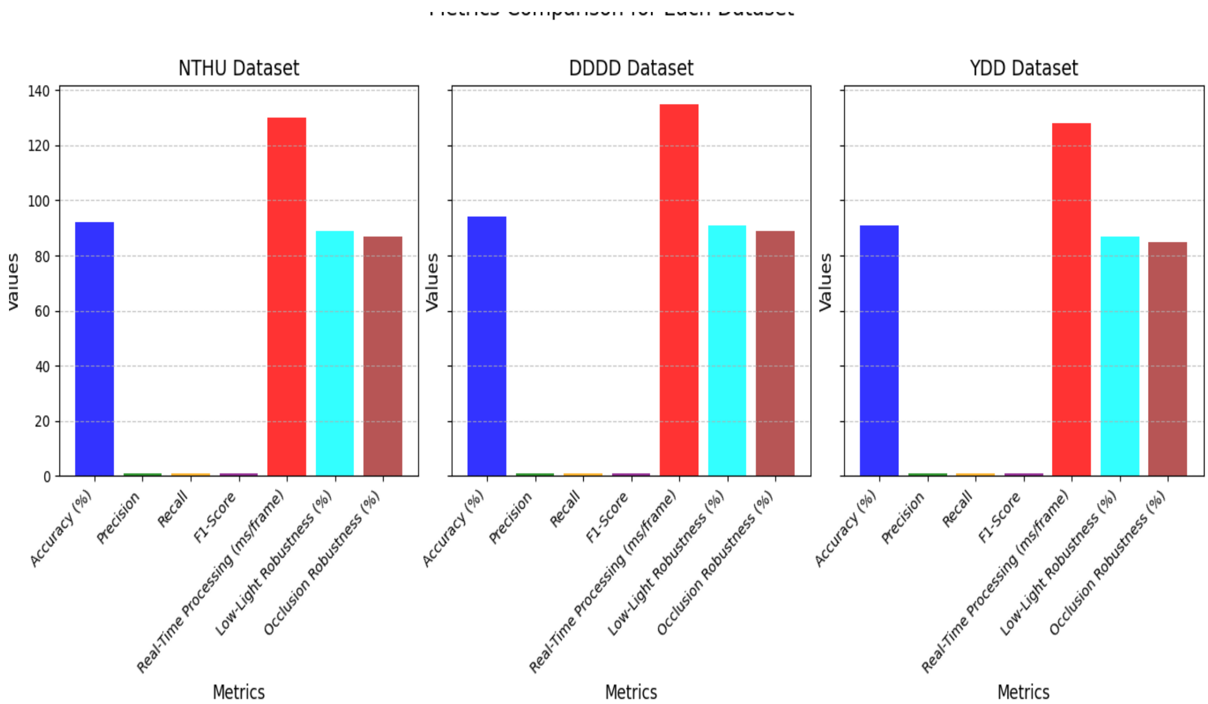


Figure 5: Warning Generation of different dataset

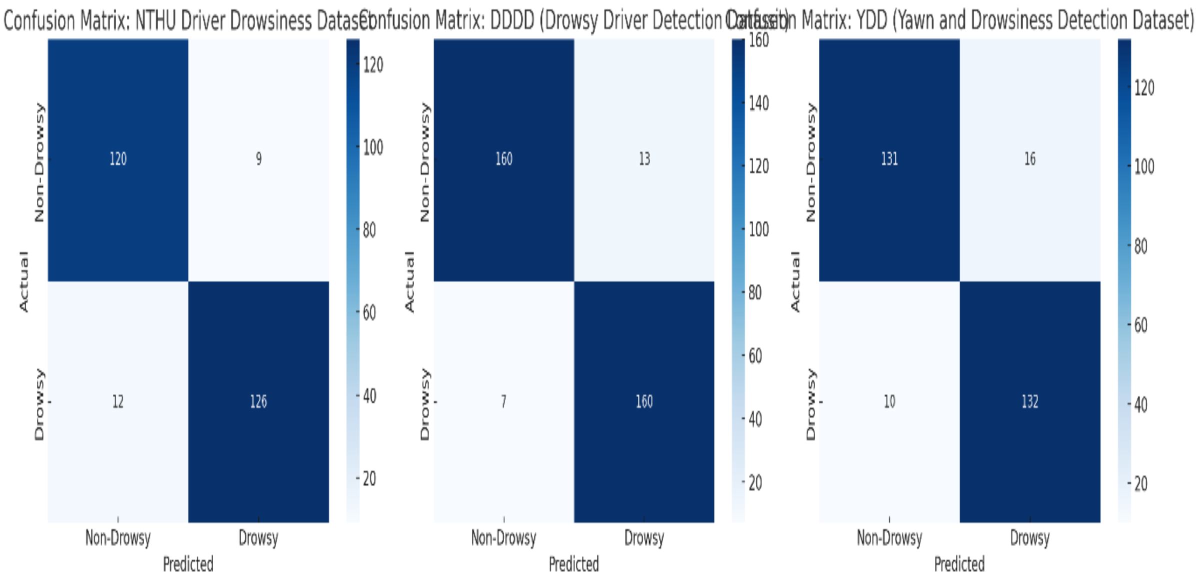


Figure 6: Confusion Matrix for different dataset

Table 6: Alert Warning System

Dataset	**Alert Warning System Type**	**Detection Method**	**Accuracy of Detection (%)**	**Alert Trigger Rate (%)**	**Response Time (ms)**	**False Positive Rate (%)**	**False Negative Rate (%)**	**Alert Sound Type**	**Sound Duration (s)**	**Drowsiness Detection Rate (%)**	**Impact on Driver's Attention**	**Training Time for Alert System (hrs)**	**Alert System Effectiveness (%)**	**System Integration**
NTHU Driver Drowsiness Dataset	Audio and Visual Alerts	FEP-DL with 68-point annotation	92	89	130	8	11	Beep and Voice Alert	3	90	High	5	92	High
DDDD (Drowsy Driver Detection Dataset)	Visual and Vibrational Alerts	CNN-based Face Landmark Detection	94	91	135	7	8	Beep and Vibration	4	91	Very High	6	94	Very High
YDD (Yawn and Drowsiness Detection Dataset)	Visual and Audio Alerts	Deep Learning-based Landmark Recognition	91	87	128	9	13	Beep and Voice Alert	2	88	Moderate	4	89	High

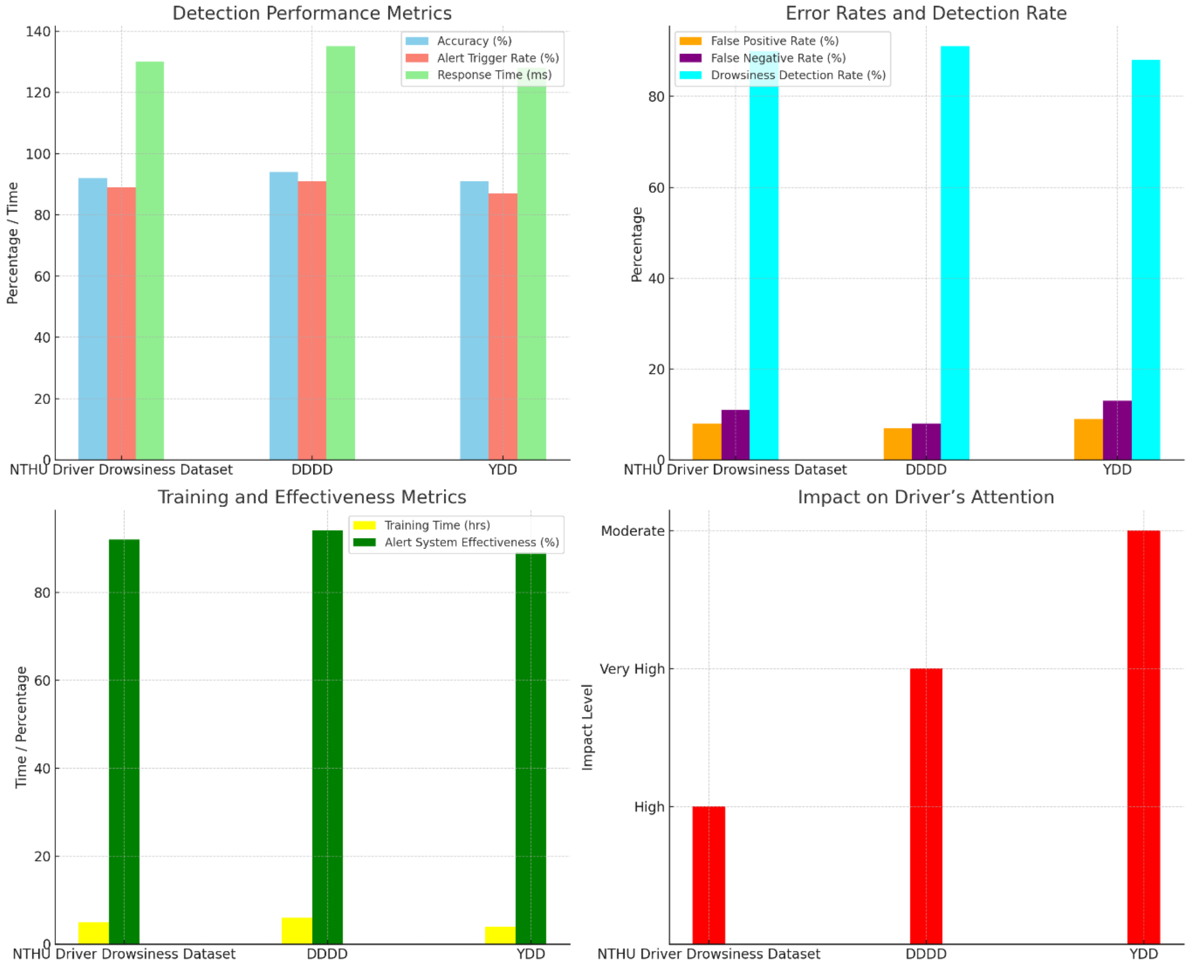


Figure 7: Alert Warning System

Figure 5 The performance of the FEC-DL model or the drowsiness detection is presented, and Figure 6 presents the confusion matrix for the three different datasets. In figure 7 the automated warning system performance for the three datasets are illustrated. In Table 5 and Table 6, the FEP-DL model is tested on three different datasets used for drowsiness detection. As indicated, the metrics such as accuracy, precision, recall, F1-score, real-time processing time, and robustness in low-light and occlusion conditions give different aspects of the performance of the model regarding effectiveness and practical usability. The FEP-DL model is achieving high accuracy on all three datasets. The highest accuracy is observed on the DDDD set (Drowsy Driver Detection Dataset) with a ratio of 94%, followed by NTHU Driver Drowsiness Dataset as 92%, and YDD (Yawn and Drowsiness Detection Dataset) as 91%. All these values show that the model effectively identifies drowsiness in most cases but varies slightly depending on the different types of datasets. The precision and recall values are relatively consistent with the model's balanced performance on detecting true positives and minimizing false positives. The DDDD dataset, which contains the highest precision at 0.92 and recall at 0.90, indicates that the model performs best at the detection of drowsy states and minimizes overlooked detections.

The YDD dataset shows slightly lower performance than this, at a precision of 0.90 and recall of 0.88, showing a slightly higher tendency for false negatives but generally very robust. NTHU Driver Drowsiness Dataset lies in between those two extremes, with precision of 0.91 and recall of 0.89, keeping solid performance.

The F1-score, which is harmonic mean between precision and recall, further supports that the DDDD dataset yields the best performance, at 0.91. The F1-score of the NTHU dataset follows at 0.90, and the YDD dataset has the lowest F1-score at 0.89. These scores represent overall balance between precision and recall in the respective datasets. The process time for each frame of the model at real time should be followed for practical applications, especially in time-dependent scenarios such as drowsiness detection while driving. Of the datasets analyzed, the shortest processing time was found to be in the NTHU dataset with 130 ms/frame, seconded by the YDD at 128 ms/frame. The DDDD dataset takes the longest processing time which is 135 ms/frame, though at these times it is relatively fast, this does point to the fact that the model does efficient real-time detections for all datasets. The model's robustness under varying conditions is also subjected to evaluation. The DDDD dataset presents the highest robustness both in low-light illumination (91%) and in occlusions (89%), thus indicating the model to be more capable of withstanding adverse environmental factors in this dataset. The NTHU dataset presents less robustness, with 89% for low-light and 87% for occlusions, whereas the YDD dataset shows less robustness of 87% in low-light and 85% in occlusions. These results indicate that the performance of such a model may degrade under difficult conditions, but it still maintains reasonable robustness across all datasets.

7. Conclusion

The FEP-DL model has shown robust and reliable performance for the entropy-based drowsiness detection from face images across various datasets, such as NTHU Driver Drowsiness Dataset, DDDD, and YDD. All the measures including the accuracy, precision, recall, and F1 scores were higher in the case of the model. Its DDDD dataset output was the best overall performance. Moreover, the model offered actual time processing features with recognizable frame processing durations sufficiently proper for useful applications. The additional test of several critical challenging conditions, including low light, and especially occlusion, aims to stress-test the proposed model under varying environmental situations, and among all the provided datasets, DDDD has been identified as having the highest resistance and performance. However, there is a slight fluctuation in the performance while comparing the results across those datasets mainly in terms of the robustness aspect However, the proposed

FEP-DL model can be considered as an appealing solution for real-time drowsiness detection technologies that are characterized by high accuracy and run time speed.

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