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LBP-CNN Fusion for Driver Fatigue Detection

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Abstract*: Nowadays, individuals tend to rely on their own means of transportation. As the number of vehicles on the road continues to rise, the occurrence of accidents has also increased. Specifically, road accidents are becoming more prevalent, with driver drowsiness being a significant contributing factor. Approximately 2.3 lakh out of the 23 lakh road mishaps that transpire in the country each year are attributed to drowsiness. Recent data indicates that an estimated 2.3 lakh to 3.5 lakh road accidents are a direct consequence of sleepiness[9]. To mitigate the occurrence of such accidents, we propose the implementation of a drowsy detection system for drivers. This system ensures that both the passengers and the driver can embark on their journey with the assurance of safety. The system utilizes a camera to monitor the driver's facial expressions and issues alerts accordingly. It analyzes various facial features such as eye closure, yawning, and signs of fatigue, subsequently notifying the driver to remain attentive. This approach involves the utilization of the local binary pattern texture analysis method in conjunction with convolutional neural networks (CNNs). By doing so, it effectively highlights the textural variations in the driver's face, thereby clearly identifying the relevant facial features. The camera detects the driver's face, captures the image, and subsequently converts it into LBP images. This process enables the system to detect subtle indicators of drowsiness, ultimately aiding in the prevention of accidents. Consequently, this system significantly reduces the occurrence of drowsiness-related accidents, thereby saving numerous lives*

Keywords: Local Binary Pattern (LBP) texture analysis**,** Convolutional Neural Networks (CNNs), Driver Fatigue Detection, Facial Features, Prevention of Accidents

I. INTRODUCTION

In India, one major factor contributing to traffic accidents is driver fatigue. The Ministry of Road Transport and Highways Transport Research Wing reports that 3,84, 448 people were injured and 1,53, 972 lives were lost in traffic accidents in 2021. Remarkably, 18 to 45-year-olds are the age group most severely impacted by traffic accidents, making up almost 67% of all unintentional fatalities. About forty percent of traffic accidents are caused by tired drivers who nod off while operating a vehicle, according to research done on the Agra-Lucknow motorway by the Central Road Research Institute (CRRI). Additionally, daytime tiredness and fatigue while driving are significantly influenced by sleep disorders, such as obstructive sleep apnea (OSA). Sleep problems affect more than 20% of victims of traffic accidents.

Several methods and studies have been conducted to detect driver fatigue detection. Currently, three distinct groups can be distinguished based on the characteristics of the inputs for fatigue driving detection: Physiological signs, vehicle information, and facial characteristics.

In recent years, the rising number of road accidents due to driver fatigue has become a pressing concern around the world. As people progressively depend on individual transportation, the chance of accidents caused by fatigue has risen. Tending to this issue requires innovative arrangements that can successfully distinguish signs of a driver's fatigue and caution them instantly to avoid accidents. In today’s transportation systems, driver fatigue is one of the critical issues leading to a significant number of road accidents, threatening the lives of drivers and passengers. Hence, real-time identification of fatigued drivers holds the key to accident prevention and road safety. Existing methods for fatigue detection are not suitable since they extract drivers’ physiological measurements and use the angle of the steering wheel. However, these modes are unreliable and unsuited for real-time responsiveness. Driver fatigue causes accidents on the roads. There is technology to detect this when we get tired, and how it’s working is going to find the face from

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the driver's image. This work of research involves the use of a powerful method that quickly seeks out faces and reads expressions for a selective face.

In response to this challenge, the combination of local binary pattern (LBP) texture analysis with convolutional neural networks (CNNs) has emerged as a promising approach for driver fatigue detection.The LBP-CNN combination strategy leverages the qualities of both strategies to realize strong and precise detection of drowsiness indicators from facial pictures captured by onboard cameras. Nearby Binary Pattern (LBP) texture analysis could be a widely used strategy for characterizing texture patterns in pictures. It encodes local texture information by comparing the intensity of a central pixel with its surrounding neighbours, subsequently capturing critical facial features demonstrative of laziness such as eye closure, yawning, and signs of fatigue.

On the other hand, convolutional neural networks (CNNs) are powerful deep learning algorithms capable of learning complex designs and features specifically from raw information. By preparing a huge dataset of facial pictures annotated with drowsiness labels, CNNs can successfully learn to recognize unobtrusive facial signals related to fatigue, empowering computerized discovery with high precision.

The combination of LBP texture analysis with CNNs capitalizes on the complementary qualities of these two strategies. LBP gives a compact representation of local texture features, which serves as significant input to the CNN for advanced handling and learning of higher-level features. This integration improves the discriminative control of the discovery framework, empowering it to successfully capture the nuanced facial expressions characteristic of drowsiness whereas minimizing false alarms.

II. LITERATURE SURVEY

There are serious safety concerns for drivers as a result of an upsurge in traffic accidents brought on by the increased use of vehicles. Even with worldwide efforts to address this problem, significant progress has not yet been made, and accidents continue to be a serious threat to people's lives and safety. These accidents are caused by a number of things, such as driving while intoxicated, ignorance of traffic laws, and, in particular, driving when exhausted. In addition to having a substantial negative influence on driving performance, fatigue causes over 20% of all car crashes[1]. In order to reduce these accidents, this study focuses on driver drowsiness detection. Reducing the frequency of these collisions is the aim of driver drowsiness detection technologies. This is investigated using a variety of techniques, including ANN, image processing, and electroencephalograph technology [2].

Various fatigue detection techniques:

i) Images Processing based techniques

ii) EEG (electroencephalograph) based techniques

iii) Artificial neural network-based techniques

i. Images Processing based techniques

The methods based on image processing use the facial images of drivers to identify whether or not they are awake. It is possible to detect indications of drowsiness by looking at the driver's face image, particularly when their eyes are closed, which indicates that they are sleeping. These pictures also show additional signs of sleepiness. These methods can be divided into three smaller groups.

1) Template Matching Technique: This is where the system assesses the condition of the driver's eyes.[5] An alarm is set off if the driver closes their eyes for a predetermined amount of time. The way this technique operates is by using templates for the driver's open and closed eye states. Additionally, the system is trainable to identify these templates, which makes implementation reasonably easy.[6]

2) Eye Blinking-based Technique: This technique detects driver drowsiness by measuring the rate of eye blinking and the length of eye closure. The way a driver blinks their eyes and moves their gaze between their lids changes significantly when they get sleepy. This system keeps track of the eyes' positions as well as the length and frequency of blinks. Computer vision techniques locate the face, eyes, and eyelids by analyzing video feeds from a remote camera[7]. The system determines whether a driver is sleepy by dividing their frequency of blinking by their ratio of eye closure.

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3) Yawning-based Technique: Yawning is a sign of fatigue. It is distinguished by a broad vertical mouth opening that is greater than normal mouth movements made during everyday tasks like speaking. This method detects yawning by following the face and then focusing on the mouth[8]. By monitoring changes in the area of the mouth's contour and the rate at which it opens, the system detects yawns. To enhance the system's overall performance in identifying driver drowsiness, some researchers combine multiple vision-based image processing techniques instead of depending on a single one.

ii. EEG-Based Technique:

This technique uses an electrode helmet fitted with precise electrode sensors to record brain activity while a driver is behind the wheel. To identify cases of drowsy driving, researchers examine the characteristics of Electroencephalogram (EEG) signals[3]. They suggested a technique to determine fatigue levels that combines the FastICA algorithm with power spectrum analysis. EEG signals were recorded in two states in a driving simulation setup: sober and sleepy. FastICA was used to process the multi-channel signals in order to remove interferences caused by power frequency disturbances, muscle activity, and eye movements[4].

iii. Artificial Neural Network (ANN) Based Technique:

Neural networks are utilized in this method to identify driver fatigue. Since a single neuron isn't very accurate, using several neurons produces better outcomes. People who are tired display particular visual behaviors, such as altered movements of their heads, faces, and eyes. A person's level of fatigue is reflected in their gaze, facial expressions, and eyelid movements. A drowsiness-detecting artificial neural network is built to take advantage of these visual cues. They tested samples, and their accuracy rate was 96%. shows the process by which a drowsiness can be accurately detected by an artificial neural network system.

IIII. MAGE PROCESSING BASED FATIGUE DETECTION

Figure 3.1 shows the general architecture for vision-based image processing techniques for for detecting drowsiness. First, frames are extracted from a video that was taken with a camera mounted inside the car. The driver's face is detected using face detection algorithms, and the eyes are located using eye detection algorithms. Tracking algorithms are then used to track the movements of the face and eyes0020
[5]. Then, using these processed images, drowsiness is determined by examining different symptoms and applying predetermined techniques. This method has been applied in a number of research projects with the goal of creating non-intrusive computer vision and artificial intelligence-based driver drowsiness systems. These systems use cutting-edge technology to continuously track the condition of the driver's eyes, even when they are engaged in real-world driving situations. Different algorithms are used for different tasks, such as eye and face tracking, and each yields different results, such as eye detection, eye tracking precision, and face tracking accuracy. The findings of these investigations show how reliable and accurate the system is under a variety of circumstances, such as shifting lighting, external interferences, vibrations, changing backgrounds, and facial orientations. It should be noted, though, that although this system is good at detecting drowsiness, it may occasionally gives false alarms.

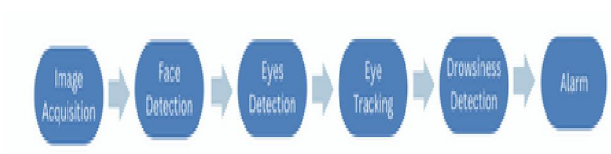

Fig 3.1 Image Processing Based Fatigue Detection

3.1 IMAGE PREPROCESSING

Before providing data to machine learning models, image preprocessing is necessary. A quick rundown of the main procedures in image preprocessing is as follows: Resizing involves adjusting an image's dimensions to a preset size, like 128 x 128 or 64 x 64 pixels. By ensuring that every image has the same dimensions, this standardization makes it

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easier to process the dataset consistently. By using manageable-sized images, it also contributes to a reduction in computational load.

When colour images are converted to grayscale, colour information is removed and representing images using shades of gray. Unlike RGB images, which have three channels—red, green, and blue, grayscale images only have one channel. By simplifying the data, this conversion lowers computational complexity without compromising important characteristics like patterns, textures, and facial expressions.

Scaling pixel values within a predetermined rangetypically between 0 and 1 is known as normalization. Pixel values are normalized to standardize the data and keep features with larger scales from controlling the learning process. Normalization helps preserve numerical stability in computations and promotes faster convergence during model training.

3.2 LOCAL BINARY PATTERNS (LBP)

The Local Binary Pattern (LBP) is a powerful method to characterise textures in images. It emphasises small textural elements and details in the image; hence, it is very effective for analysing grayscale images. Typical tasks of interest include facial expression analysis. Consider an image composed of pixels of grey values, called grayscale image. The LBP method distinguishes each of its pixels of the image and then compares it to its neighbours. After computing the differences between the intensity value of the central pixel and those of its neighbours, it computes the relationship between the central pixel with those neighbours. The computed relations allow to assign to each pixel inside the image a binary code based on those differences. By comparing the grey value of the central pixel with those of its neighbours and then encoding those relations according to predefined rules, the code is achieved.

The resulting binary relationships are then processed further to create a final LBP code that includes weighted values according to specified requirements. By using these weights, the local texture surrounding each pixel is represented in a more explaining way. By extracting LBP codes from different sub-regions within the facial expression image, LBP creates a sequence of histograms. Every sub-region adds to a series of LBP codes, which together create a distribution histogram for local texture patterns.

Ojala et al. introduced the Local Binary Pattern (LBP) operator as a technique for examining textures in images. In order to encode texture information, it looks at the connections between a pixel and its surrounding pixels for putting binary codes to pixels according to where they are located. The first step is to compare a pixel's intensity value with those of its surrounding pixels in a 3x3 window:

$$S(f_p - f_c) = \begin{cases} 1 & if \\ 0 & oth \end{cases}$$

Generating the LBP code while taking the binary relations into consideration.

$$LBP = \sum_{p=0}^{7} S(f_p -$$

Using an LBP code histogram to represent the texture of a picture. To characterize the texture, the LBP codes of each pixel in the input image are gathered into a histogram:

$$LBPH(i) = \sum_{x,y} \delta\{i, LBP(x,y)$$

Where δ(·) is the Kroneck product function

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Local Binary Patterns (LBPs) have proven to be remarkably effective in representing images for a variety of applications, including motion detection, facial expression analysis, and visual inspection. Two important characteristics of LBP features are their computational simplicity and ability to withstand regular variations in lighting. Local texture details are captured by the operator's skillful identification of various texture primitives, including spots, line ends, edges, and corners, which are then combined into a histogram.

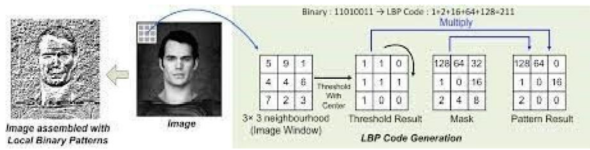

Fig 3.2LBP Code Generation

3.3 CONVOLUTIONAL NEURAL NETWORK (CNN).

Convolutional neural networks, or CNNs for short, are a subset of deep learning models that are especially useful for handling structured, grid-like data, like audio or image files.

Through convolution and pooling operations, the first layers of a CNN extract low-level features such as edges, textures, and shapes. Deeper network progression yields higher-level features, which indicate more intricate patterns and structures. Using optimization algorithms such as gradient descent, CNNs learn by tuning the weights of their neurons during a training phase in order to minimize the discrepancy between the expected and actual outputs. CNNs are an effective tool in contemporary machine learning and artificial intelligence because of their capacity to automatically extract pertinent features from raw data.

Images of the driver's mouth and eyes in a realistic driving environment frequently differ in size. The input image is scaled to 175 × 175 pixels in order to account for this. Two convolutional pooling stages are used to create a 44 × 44 × 56 feature map. The 3 × 3 kernel size and step size of 1 are used in this case for convolutional layers, and the 3 × 3 kernel size and step size of 2 are used for pooled layers.

An extra layer of pixels is filled along the image borders during convolution operations to prevent information loss at the image edges. Moreover, 3 × 3 pooling layers, 1 × 1, 3 × 3, and 5 × 5 convolutional layers are used to improve the network's ability to adjust to changes in image size. An additional stage of pooling produces a 44 × 44 × 256 feature map. This map creates an 11 × 11 × 72 feature map by passing through a residual block made up of three convolutional layers and then pooling.

Within the fully connected layer, the resulting feature map is then flattened into a one-dimensional vector. Random inactivation is used to reduce parameters in order to stop the network from overfitting. Lastly, the network uses softmax to output classification results, identifying whether the mouth and eyes in the images are open or closed.

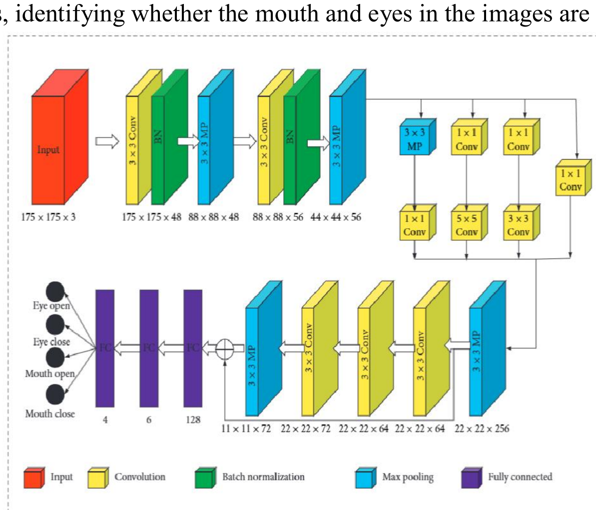

Fig: 3.3 Convolution Neural Network.

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3.4 FATIGUE CLASSIFICATION.

A driver will typically exhibit a number of physiological reactions, including eye closure and yawning, when they become fatigued. Two categories will be created by categorizing the fatigue detection from the LBP-based CNN process. The four states were predicted to be closed eyes, open eyes, yawning, and no yawning. This is the true category.

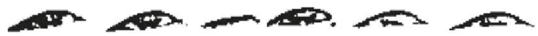

Fig 3.4.1: image showing changes of blinking process

Fig 3.4.2: image showing changes of yawning process

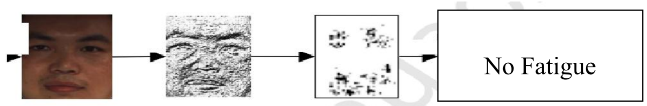

Fig: 3.4.3 Fatigue Classification

IV. EXPERIMENTAL

4.1 DATA COLLECTION & PREPROCESSING.

Local Binary Patterns and Convolutional Neural Networks are the two mechanisms that make up the suggested driver fatigue detection method. We collect samples from sources to train these networks,

Preprocess the photos to guarantee consistent and trustworthy input for analysis, such as resizing, normalizing, and data augmentation. Fig 4.1.1 shows the detection of the drowsiness when eyes are closed and if there is yawning

Fig:4.1.1 Drowsiness Detected.

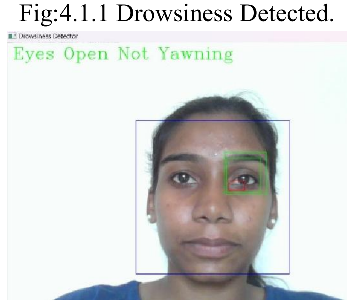

Fig:4.1.2 No Drowsiness.

4.2 EVALUATION

Testing in machine learning is assessing a trained model's performance on fresh or untrained data. Understanding the model's capacity to generate precise predictions outside of its training set of data requires completing this step. Testing evaluates the accuracy, robustness, and fit of the model for the purpose for which it was designed. Samples from the training set's data distribution are included in the testing dataset, which is separate from the training and validation sets.

Verifying that the model's learned patterns remain consistent regardless of how frequently the program is used is the main goal of machine learning testing.

V. CONCLUSION

Convolutional Neural Networks (CNN) and Local Binary Patterns (LBP) are combined in the driver fatigue detection project to identify symptoms of fatigue in real-time, such as yawning and closed eyes. This combination guarantees precise driver state classification even in the presence of variations in lighting and facial expressions. Its efficacy is demonstrated by real-world testing, and a testing framework based on tables makes it easier to track performance in various scenarios, thereby increasing road safety.

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