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AI-Based Intelligent Traffic Management System and Accident Detection System

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***Abstract*—Fatigue, drowsiness, and sleepiness are often used interchangeably when describing the driving condition. It is multifaceted in nature, including many human variables, and has proven challenging for academics to describe throughout the last decades. Regardless of the ambiguity associated with tiredness, it is a significant element in driving safety. Fatigue is a major cause in road accidents globally, according to studies. It is especially important for occupational drivers, such as bus and heavy truck drivers, since they may be required to operate for an extended length of time during peak sleepiness times. Driver tiredness or sleepiness is a significant contributor to road accidents. Fatigue is a term that refers to a state of diminished ability, which may be physical or mental. While fatigue may be caused by a variety of external causes, sleepiness is a natural condition associated with the desire to sleep. As a result of the complexity and diversity of fatigue characteristics, identification may be more challenging. In this work, driver drowsiness is detected using eye and mouth detection with Euclidean distance measurement and SVM classifier**

***Index Terms*—Driver Drowsiness Detection System, Support Vector Machine, Machine Learning, Electroencephalogram, Electronic Control Unit, Internet of Things, Intraocular Pressure**

I. INTRODUCTION

Nowadays, an increasing number of occupations demand prolonged attention. Drivers must maintain a constant eye on the road to respond quickly to unexpected occurrences. Driver tiredness is often a direct cause of many traffic accidents. As a result, technologies are needed to identify and alert drivers to their poor psychophysical state, which may substantially decrease the frequency of fatigue-related vehicle accidents. However, the development of such systems faces many challenges linked to the rapid and accurate detection of a driver's tiredness symptoms. A vision-based method is technological option for implementing driver sleepiness detection systems. This work discusses the many drivers' drowsiness detecting technologies presently in use. We are identifying the driver's sleepiness in this case by evaluating his visual system. Due to the fact that driver drowsiness and lack of alertness are the leading causes of traffic accidents, particularly for drivers of large vehicles (such as cars, buses, and heavy trucks) due to extended driving periods and lack of sleep, there is a need to develop a system that performs a function in terms of accident reduction. The purpose of this article is to present a vision-based sleepiness and non-alertness detection system for driver monitoring that is simple to install and adaptable to all types of cars. Life as hurried can be fraught with danger. Following that, security precautions should always be performed prior to any kind of catastrophe writing occurring. Street mishaps are one of the primary causes for perpetual infirmity in these times. Each second counts or is essential to your safety while driving. A single moment of inconsideration may result in a lifetime of regret. The overwhelming majority of studies conclude that most street collisions occur because of the driver's lack of attention and tardiness. Drowsiness Detection System was developed using machine vision concepts. The framework makes use of a small camera that is pointed directly at the driver's face and monitors the driver's eyes to differentiate between fatigue and sleepiness. (When tiredness is detected, an admonish sign or warning signal is shown to alert the driver to awaken and exit the weary condition. The framework first identifies the face, then the eyes, and finally determines whether the eyes are open or closed.

II. RELATED WORK

When in doubt, a significant part of the population does not adhere to any of the above laws, and it is very inconvenient for a traffic Police authority to reject the motorist with any of the above laws on any occasion. [1]-[3] And here is where development comes into play; a plethora of gadgets have been developed far and wide to circumvent this explanation, but the most of them are prohibitively expensive or unavailable at the local show. [4] Driver language finding is a vehicle prosperity advancement that averts catastrophes when the driver becomes exhausted. [5] According to several studies, about 20% of all traffic fatalities are caused by fatigue, with up to half occurring on expressways 6] According to recent estimates, shortcoming-related incidents regularly result in 1,200 deaths and 76,000 injuries. The development of technologies for detecting and preventing driver fatigue is a key test in disaster prevention systems. [7] use to the threat that sluggishness poses everywhere, techniques for eliminating its possessions should be developed. [8] Driver in thought may be the result of a lack of attention to detail when driving because of driver sluggishness and interference. When anything or someone obscures a person's view of the driving effort, this is called driver interference. [9] Unlike driver interference, driver fatigue does not include a concurrent starting event; rather, it is characterized by a distinct disengagement of mind from the road and traffic needs. In any instance, both driver sluggishness and interference may have similar consequences, namely worse driving execution, increased response time, and an increased risk of accident incorporation. Considering the acquisition of video from the camera in front of the driver, consistent preparation of a moving toward video stream is performed to stimulate the driver's level of fatigue. If the driver's level of laziness is estimated, the yield is sent to the ready system and the alert is initiated. [10]

Gole et al. [1] A driver's alertness is a critical element that must be constantly checked. A sleepy driver may cause a variety of errors and accidents on roads, resulting in financial loss, bodily damage, and, most importantly, the loss of human life. Drowsiness detection system is a kind of vehicle safety technology that assists in preventing and therefore minimizing accidents caused by sleepy driving. The system is intended for four-wheeler vehicles (or more) and detects and warns the driver to tiredness or sleepiness.

III. SYSTEM ARCHITECTURE

Islam et al. [2] Human-caused accidents are steadily rising, and one of the leading reasons is driver sleepiness. Thus, to reduce accidents caused by sleepiness, researchers have developed techniques that use facial expressions to identify drowsiness in recent decades

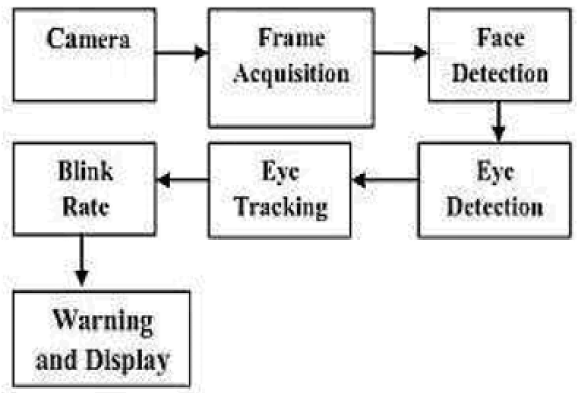


Figure 1: Basic Block Diagram for Alert on Drowsiness

However, the most advanced versions are only capable of detecting driver sleepiness and alerting the driver.

Jadhav et al. [3] Accidents are a significant problem these days. There are two primary reasons for this: Numerous accidents occur because of intoxicated drivers' reckless driving. The second kind of accident happens because of the driver’s-tired eyes caused by driving long distances in the dark while not getting enough sleep.

Arunas Alam et al. [4] the incidence of traffic accidents caused by microsleep has risen alarmingly in recent years. Individuals may fall asleep without recognizing it during microsleep. For many decades, drowsiness detection systems for cars were not a priority, even though they are one of the critical elements that might have prevented microsleep and should therefore be installed in all vehicles to guarantee the safety of drivers and other road users. To author knowledge, no enforcement of driving restrictions while in a drowsy condition has been undertaken.

Biswal et al. [5] in recent years, sleepy driver identification has become the most critical technique for preventing any traffic disaster, most likely globally. The purpose of this research was to develop a smart warning method for use in developing intelligent cars that can detect and prevent sleepy driver impairment automatically.
Driver sleepiness is a leading cause of accidents. Around 50% of accidents occur on the road. Driver sleepiness has become a significant cause of road accidents. Certain techniques must be devised to keep the driver awake while driving. This has become a significant difficulty in terms of developing a strategy for preventing this problem. Rather than limiting sleepiness, it is suggested to build a system for detecting driver weakness on an infinite scale. It continuously monitors the driver's level of sleepiness and generates a signal when the level exceeds a certain value. This signal controls the vehicle's water-powered slowing mechanism. Thus, developed an anti-collision framework based on languid driving identification and endeavored to keep an eye on developing advancements and choose the finest methods for trying to avoid the primary cause of fatal automobile accidents.

The main objectives of this thesis are

- To implement SVM classifier-based driver drowsiness detection system using python
- To implement eye and mouth i.e., yawn and eye closing method for training SVM
- To improve the performance by using Euclidean distance as input parameter for advanced SVM

SVMs learn through supervised classification and regression techniques. SVMs were first presented in 1992 by Boser, Guyo, and SVMs are tasked with the task of determining a hyperplane that splits the training data into predetermined pathways. SVMs are mostly used in driver sleepiness to detect the different driving states from specified data. Numerous attempts have been made to identify sleepiness using SVMs. SVMs were utilized to evaluate driver sleepiness rate using several metrics. The binary SVM classifier is used to determine whether the driver is sleepy. These characteristics aided in the development of a more effective driver sleepiness detection system.
Support-vector machines (SVMs, also known as support-vector networks[1]) are supervised learning models that evaluate data for classification and regression analysis. SVMs are a collection of supervised learning techniques for classification, regression, and outlier identification. Even when the number of dimensions exceeds the number of samples, the method is still successful

Versatile: a decision function may be defined using a variety of Kernel functions. While standard kernels are included, custom kernels may also be specified.
Support Vector Machine, or SVM, is a widely used Supervised Learning method for Classification and Regression issues. However, it is mainly utilized in Machine Learning for Classification issues.

IV. ACQUIRING DATA

The SVM algorithm's objective is to find the optimal line or decision boundary that partitions n-dimensional space into classes, allowing us to easily classify additional data points in the future. This optimal decision boundary is referred to as a hyperplane.
SVM selects the hyperplane's extreme points/vectors. Support vectors are used to refer to these extreme situations, and therefore the technique is named a Support Vector Machine.

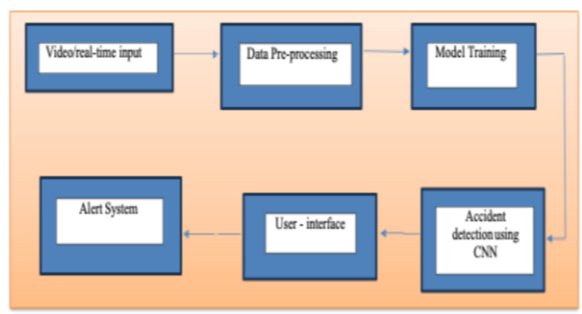


Fig 3.1 System Architecture Diagram

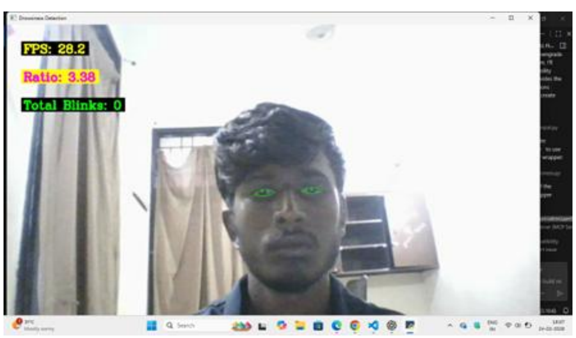
Table I. Feature vector for Support Vector Machine

techniques are proposed on the 2-dimensional picture of the recorded video. Now, the required driver information is produced. The volunteers are asked to focus on the laptop webcam and perform activities like continual eye blinking & closing, mouth yawning, and head bending. And the webcam is adjusted to capture the video for 20 to 30 min.

V. FACE IDENTIFICATION

The driver's face is identified first after the frames have been extracted. In this paper, HOG & SVM algorithms [10] are used for face extraction. In this detection, only positive examples of the stable window sizes are taken for photographs and histogram of oriented gradients (HOG) descriptors are calculated on them. Following that, the negative examples of same size are considered for HOG descriptors and then results are evaluated. Typically, the count of negative examples is more than positive examples. Then after getting the characteristics of both the groups, a direct SVM algorithm is used for classifying the required task. To get more detection and better accuracy for SVM algorithm, strong negatives are used. In this detection, after the guidance, the SVM classifier is investigated on labeled data and the incorrect positive example characteristic values are reused for guidance purpose. To test the picture, the window used for positive examples are rendered over the image and then the required result or output will be classified for each window location. Then based on the results obtained and considering the various sample results, the higher value samples are considered for drowsiness identification and the boundary outline is drawn on the face. This minimum elimination steps will reduce the overlapping and redundant bounding in the bounding box.

VI. LOCATING FACE POINTS



After the detection of faces, the further step is to locate the points on the human face like eyes, mouth, nose etc. Then the photograph that used for face detection must be normalized to minimize the distance factor between camera and the driver. Therefore, the face photograph is resized with the width of 500 pixels and converted into gray scale pictures. Then normalization is done for regression trees [11]. And it will be approximate the positions of location points on the face from pixel intensities. In this process, the square error loss is reduced by using gradient boost learning. Different priors are used to discover various structures. By considering this procedure, the location of the boundaries of eyes, mouth and nose are noted and shown in Table I. Then the location points on face are marked and shown in fig.2. The red points on the figure are used for further identification.

VII. FEATURE EXTRACTION

After marking the points on face, the drowsiness features are calculated as given below. Eye Aspect Ratio (EAR): From the boundary points on the eyes, the EAR is evaluated as inverse ratio of width of eyes to the height of eyes. The mathematical formula for EAR is given as,

$$\mathbf{EAR} = \frac{(p2-p6)+(p3-p5)}{2(p4-p1)}$$

where i is the point marked as i in facial landmarking (i − j) gives the distance between the points i and j.
When the eyes are open EAR is max and when the eyes are closed, the EAR is approximated to zero. So, the decreasing value of EAR indicates the closing of eyes and identifies the drowsy behaviour of the driver.
Mouth Opening Ratio (MOR): Mouth Opening Ratio is defined as the identification of yawning of the driver and ultimately drowsiness detection is done. The mathematical formula for calculating the MOR is given as,

$$\mathbf{MOR} = \frac{(p15-p22)+(p3-p5)+(p23-p21)}{2(p19-p13)}$$

The MOR ratio is maximum when the mouth of driver is open and if it remains same for some time, then yawning condition is indicated. And if it decreases towards zero, then the condition is considered as normal, and not yawning. Nose Length Ratio (NLR): When the head of the driver is down along with vertical axis, then by using the bending angle of head the drowsiness alert is identified. The focal plane of the webcam is directly proportional to head bending, and by using this head bending is calculated.
Normally, the nose makes an acute angle with the webcam. The acute angle increases when head moves upward and vice versa. Therefore, the nose length ratio

is given as nose length to average length of nose, which also measures the head bending.

VIII. CLASSIFICATION

After obtaining the values of eyes, mouth and nose, the next step is to identify the drowsiness from the SVM frames. The flexible value of threshold is required for the drowsiness. Then, algorithms like SVM are used for the classification of the information. For obtaining the threshold values for eyes, mouth and nose the initial condition of the driver is assumed to be in normal state. This step is known as setup phase. The EAR for nearly 100 to 300 frames will be recorded, and from this an average of 150 to 200 higher values are recognized as strong threshold values for EAR. The values which are high i.e., in which eyes are not closed is considered. If threshold is more than the tested value, then it is identified as eyes closed. For every person, the size of eye will be different; so, this makes the impact to decrease the setup for person to person. For computing MOR values, the threshold value of frames is calculated based on the condition that the mouth is not open. If the threshold is less than the test value i.e., when the mouth is open, the yawning is identified. Using the head bending feature, the angle between access and head can be determined in terms of nose length ratio. NLR values range from 0.8 to 1 in normal condition of head and varies with head bending up and down. The average of the NLR is measured as mean of lengths of nose in the setup assuming that head is not bend. After obtaining the threshold values, it is tested. Then, if at least one of the eyes, mouth and nose identifiers are not satisfied, then drowsiness alert is indicated. In practical, for example out of 75 frames at least 70 frames satisfy drowsiness conditions for one or more features, then the overall system is identified as drowsiness detection and the driver is alerted with the alarm sound.

To overcome the thresholding problem, a single value of threshold is considered, and this threshold value depend on EAR. To obtain the average value of EAR, 150 higher EAR values from 300 frames are considered. If the threshold value is more than EAR value, then the driver is at danger. By considering yawn and head bending, this EAR threshold will be increased, and it is dispersed into more frames. The yawning and head bending frames are combined to get flexible value of threshold. If EAR value is more than obtained threshold value, then that condition is treated as drowsiness, and this indicates to alert. In head bending situation, if the head is down, then the frames are considered for a drowsiness alert. Table II shows the calculated parameters. The machine learning algorithms and the threshold factors are used for the identification of driver's drowsiness, from the values obtained from EAR, MOR, and NLR. Earlier, these features were used for the analysis of classification from feature space to individual. However, here it is used for the principal component analysis [12].

After converting the values obtained from threshold, whether the features are significant for classes or not is tested. If three factors give five percent significance, this classification based on Bayesian Classifier and SVM algorithm is used [12].

IX. RESULTS AND DISCUSSION

The webcam of the laptop is turned ON and the face of the driver is recorded and captured. The captured video is transferred to the processing block to identify the drowsiness detection. If mishap is detected, then alarm will buzz a sound to alert the driver. The initial state of driver condition is given in Fig. 3. For this frame the values are given as,

EAR= 0.350, MOR= 0.341, NLR= 1.030
(milliseconds, n=28.2).

Data preprocessing is a process of preparing the raw data and making it suitable for a machine learning model. It is the first and crucial step while creating a machine learning model. When creating a machine learning project, it is not always a case that we come across clean and formatted data. And while doing any operation with data, it is mandatory to clean it and put it in a formatted way. So, for this, we use data pre-processing tasks.

A real-world data generally contains noises, missing values, and maybe in an unusable format which cannot be directly used for machine learning models. Data preprocessing is required for cleaning the data and making it suitable for a machine learning model which also increases the accuracy and efficiency of a machine learning model.

Data preprocessing is an important step in the machine learning process. The phrase "garbage in, garbage out" is particularly applicable to data mining and machine learning projects. Data-gathering methods are often loosely controlled, resulting in out-of-range values,

impossible data combinations and missing values, etc. Analyzing data that has not been carefully screened for such problems can produce misleading results. Thus, the representation and quality of data is first and foremost before running any analysis. Often, data preprocessing is the most important phase of a machine learning project, especially in computational biology endpoint hosting dominates the cost at 98.9% of the total, since ml.t2. medium instances run continuously regardless of traffic volume. For workloads with predictable low-traffic periods, SageMaker Serverless Inference could reduce costs substantially by scaling to zero during idle periods, at the expense of cold-start latency.
If there is much irrelevant and redundant information present or noisy and unreliable data, then knowledge discovery during the training phase is more difficult. Data preparation and filtering steps can take a considerable amount of processing time. Data preprocessing includes cleaning, Instance selection, normalization, transformation, feature extraction and selection, etc. The product of data preprocessing is the final training set.
Data preprocessing may affect the way in which outcomes of the final data processing can be interpreted. This aspect should be carefully considered when interpretation of the results is a key point. It is the first and crucial step while creating a machine learning model.

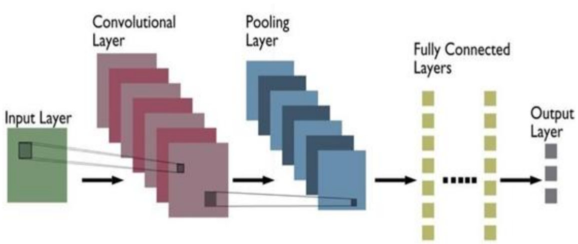


Fig. 2. 2 Architecture of CNN

B. Multi-Layered Flow with Face Verification
The "Accident Detection and Alert System" utilizing Convolutional Neural Networks (CNN) can be divided into two fundamental modules: the Real-time Detection module and the Alerting and Response module.

X. MODULES

The Real-time Detection module is designed to continuously analyze video streams from sources like webcams or surveillance cameras. It leverages pre-trained CNN models to detect and classify video frames as either "Accident" or "No Accident" in real-time. This module is responsible for the system's core functionality, enabling it to swiftly identify and pinpoint potential accidents or hazardous situations as they occur.
The Alerting and Response module, on the other hand, takes immediate action upon the detection of an accident. It is equipped with alerting mechanisms that send notifications to designated recipients through SMS via services like Twilio, sound audible alarms to draw attention to the situation, and display visual alerts for rapid response. This module serves as the link between the detection process and the system's response, ensuring that relevant parties are informed and able to take appropriate actions in a timely manner. Together, these two modules create a comprehensive and effective Accident Detection and Alert System powered by CNN technology

A. Real-Time Detection Module
Under the "Real-time Detection" module for the Accident Detection and Alert System, various sub-modules play key roles in processing and analyzing video frames in real-time.

Image Processing: This module encompasses several essential image processing tasks to prepare the video frames for analysis. Gray scaling is performed to convert the frames into grayscale images, reducing their dimensionality and simplifying subsequent processing. Normalization ensures that pixel values fall within a standardized range, making it easier for the machine learning model to work with the data. Image resizing is applied to standardize the frame size, facilitating consistent feature extraction and analysis. Finally, dimensionality reduction techniques may be employed to reduce the computational load and improve processing speed, while retaining critical information from the images.

Object Detection: In this module, Convolutional Neural Networks are employed as the primary technique for object detection within the real-time video frames. CNNs can learn and identify features and objects within images. Pre-trained CNN models or custom CNN architectures can be used for this purpose. The network is trained on relevant object classes, such as vehicles, pedestrians, or other objects of interest for accident detection.

The CNN-based object detection process involves passing each video frame through the neural network, which then generates bounding boxes or heatmaps indicating the presence and locations of detected objects. This information is crucial for identifying potential hazards or relevant elements within the video feed, which is a fundamental step in the accident detection process.

Feature Extraction: Feature extraction involves capturing essential information from the video frames that can be used for accident detection. Techniques like edge detection, color analysis, or texture feature extraction may be used to preprocess the images and extract relevant features. These features are then used as input for machine learning algorithms that determine whether an accident is occurring

Accident Detection: In this stage, the system processes a directory containing "No Accident" images. For each of these images, it reads, preprocesses, and stores the image data within a matrix (e.g., `mean_ vector _matrix`). A label of `1` is assigned to these images, indicating the "No Accident" class. This data preparation step is essential for training a machine learning model for accident detection, as it creates a dataset with labeled examples that the model can learn from. Progress updates are printed at intervals, such as every 40 images processed, to keep track of the data preparation process and to provide transparency about the system's operation

B. Smart Contract Interaction

The smart contract interaction module is a pivotal component that facilitates the seamless execution of agreements between project creators and backers. This module enables both parties to interact with smart contracts, which are self-executing agreements embedded in the blockchain. For creators, it allows the setup and management of smart contracts that define the terms, milestones, and funding conditions of their campaigns. Backers, on the other hand, can interact with these smart contracts by contributing funds, tracking campaign progress, and ensuring the automatic release of funds to creators when predefined goals are met.

XI. CONCLUSION

The proposed system is used to detect road accidents. When an accident is detected, an alert message is sent via SMS to Emergency mobile phones. This system is more reliable and economical when compared to existing systems. It can detect accidents with high level of accuracy as the model architecture is trained using the created dataset. Our preliminary evaluation shows that the system works in a perfect manner and can be deployed over a large area. With the help of this system, immediate action can be taken by sending alert to the officials and will help the local authorities to reach the accident spot in time and save the valuable human lives. Thus, the proposed system will play an important role in the society where road accidents have nowadays become a major threat.

XII. FUTURE WORKS

In an era marked by rapid technological advancements, the Accident Detection and Alert System, powered by Convolutional Neural Networks (CNN) for accident detection and real-time SMS alerts, stands as a testament to the potential of AI in enhancing safety. While the system has already showcased its capacity to mitigate the impact of accidents by swiftly alerting authorities and responders, the horizon for possibilities stretches wide, inviting future enhancements and works to further refine and extend the system's capabilities. This exploration delves into the exciting realm of what lies ahead for the Accident Detection and Alert System, offering a glimpse into the innovations and developments that promise to reshape the landscape of road safety.

A. Multimodal Data Fusion

Incorporate additional sensory data, such as audio and sensor data, to enhance accident detection accuracy. Integrating data from microphones, accelerometers, or vehicle sensors can provide a more comprehensive understanding of the accident context.

B. Advanced Alerting Mechanisms

Expand alerting options beyond SMS to include notifications through mobile apps, automated emergency calls, or integration with smart vehicle systems that can take preventive actions.

C. Cloud-Based Scalability

Transition to cloud-based architecture for scalability, enabling the system to handle a larger number of cameras and locations efficiently.

D. Machine Learning Updates

Continuously update and retrain the CNN models with recent accident data to improve accuracy and adapt to changing traffic conditions.

E. Predictive Analytics

Utilize historical data and real-time conditions for predictive accident analysis. This can help in anticipating potential accident-prone situations and taking preventive measures.

F. Real-Time Traffic Management

Utilize data from the system to manage traffic in real time, potentially rerouting vehicles to prevent congestion and improve emergency response times.

G. User-Friendly Interfaces

Develop intuitive interfaces for system administrators and end-users to monitor and manage the system effectively. Expanding the user interface for additional features to make it more efficient

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