Real-Time Driver Drowsiness Detection Using Mobile Net for Road Safety Enhancement

Muthyamaina Pavan kumar  
UG Scholar, Dept. of IT  
Sree Vidyanikethan

Engineering College  
Tirupati – 517102, A.P, India  
 [muthyamainapavankumar@gmail.com](mailto:%20muthyamainapavankumar@gamail.com)

Shaik Ayesha  
UG Scholar, Dept. of ITSree Vidyanikethan

Engineering College  
Tirupati – 517102, A.P, India  
[skayesha9553@gmail.com](mailto:mopuriyamunayadav@gmail.com)

Mallavarapu Sravika  
UG Scholar, Dept. of ITSree Vidyanikethan

Engineering College  
Tirupati – 517102, A.P, India  
 [sravikamallavarapu1676@gmail.com](mailto:mopuriyamunayadav@gmail.com)

Ms.Chengamma Chitteti  
Assistant Professor  
Dept. of Data Science  
Mohan Babu University (Erst While Sree Vidyaniketan Engineering College) Tirupati – 517102, A.P, India  
[sailusrav@gmail.com](mailto:sailusrav@gmail.com)

Dungavath Sridhar Naik  
UG Scholar, Dept. of IT  
Sree Vidyanikethan

Engineering College  
Tirupati – 517102, A.P, India  
 [sridhar2736@gmail.com](mailto:calveensai@gmail.com)

Vangipuram Anil Kumar  
UG Scholar, Dept. of IT  
Sree Vidyanikethan

Engineering College  
Tirupati – 517102, A.P, India  
 [anilkumarvangipuram321@gmail.com](mailto:avignathareddy@gamail.com)

*Abstract*—**According to research we do know, one of the top three causes of accidents on the roads all over the world is driver fatigue! In this work, we propose a real time driver sleep detection system using MobileNet, a light weight convolutional neural network (CNN) architecture that is systematically designed for mobile and indoor environments. The system scans the driver’s face in real time for drowsiness indicators, such as prolonged blinking or yawning, that could lead to drowsiness. The low cost of MobileNet means it is fast, and can be implemented in vehicles without sacrificing accuracy. This reduces fatigue and improves overall safety, as it offers immediate feedback through the instant alert model. They is cost-effective, easily run on a mobile device and scalable, making it a perfect fit for the modern-day vehicle safety needs. Fatigue signs to avoid accidents. Drowsiness slows down, and alertness, speeding it up; thus this increases the risk of accidents. Physical signals that systems often rely on require close proximity to the driver which can be distracting. To address this problem, in this paper, we use an imaging-based dataset that is measured by the driver eye movement behavior. MobileNet's model works effectively to eliminate the optical image as well, but is cost-effective which enables the visual fatigue to be passed more quickly. Based on the results, we found that MobileNet model combined with k neighbor classifier can achieve 99% performance. Besides, the system detects, tiredness in 0.00829 seconds. Hence, it is a great example for real-time. Hyperparameter tuning and k fold validation lead to a better performance. The study is a big deal considering its implications in terms of responsible driving, as it can easily be deployed as an effective way to save lives from yet another killer on the road for something as random — and unpredictable — as a seizure.**

*Keywords— Road Safety, Real-Time Detection, Deep Learning, Eye Movement Imagery, Automotive Safety, Machine Learning, Embedded Systems, Transfer Learning, Accident Prevention, Lightweight Neural Networks, Driver Monitoring System.*

# Introduction

Crucially driver drowsiness is one of the major causes attributable to road safety problems, responsible for a high rate of traffic accidents worldwide. When exhaustion is present behind the wheel, key driving functions compromised including attentiveness, reaction time and decision-making – increasing your likelihood of accidents.

These figures are rarely broken down by the cause of

fatigue – although drowsiness is suggested as a contributing

factor in thousands of vehicle injuries and fatalities every year, this should be an obvious risk. This has led to the development of sophisticated technology designed to detect driver fatigue in real time, offering a way for drowsiness-related accidents.Conventional means to detect drowsiness, however, typically require physiological signals (e.g., measurement of heart rate or EEG) due to their inherent ability. Although such approaches can provide accurate fatigue assessment, they often involve direct driver alertness probing characterized by regular contact with the person behind the wheel limit their wide spread utilization and continuous system functionality during extended durations of time in road vehicles. Furthermore, such systems might interfere with the driving experience and necessitate extra hardware to be built into a vehicle-- Over the past few years, Artificial Intelligence (AI) and Machine learning (ML) have made their implementation more costly and complex. help open up new vistas to non-intrusive driver drowsiness detection systems. These systems intent to recognize the driver behaviors such as eye movements, blinking patterns or facial expressions by means involve no physical contact. In identifying these more subtle manifestations deep learning methods have excelled, as they do possess a robust ability to analyze visual data.Deep learning is a specialized form of machine learning that has shown great promise in areas like image recognition and pattern detection; Convolutional neural networks (CNN) are essentially deep models specifically designed to work well with spatial data. One of the limiting factors in building a real-time drowsiness detection system is the need for both accuracy and efficiency, which are essential to deploy it on mobile and embedded platforms like those found inside vehicles. This requires the use of lightweight deep learning architectures that are capable of good detection tasks on this resource- constrained environments and produce a relevant speed versus reliability tradeoff.

One of these new neural nets is MobileNet, a lightweight convolutional architecture that has been specifically designed to make computationally limited mobile and embedded systems. Weird because it uses depth wise separable convolutions which strike the balance between accuracy and efficiency parameters/ops they consume for processing. That makes MobileNet an ideal choice for application that run in real-time because of its speed and resource friendly.

In this paper, we present a real-time driver drowsiness detection system built on MobileNet architecture which is tailored for automotive settings. The system pays attention to visual markers of fatigue, such as eye movements and facial expressions, so that no invasive physiological sensors are necessary in order for drivers signals. By using the lightweight & scalable nature of MobileNet, we can easily deploy it inside modern vehicles where availability and deployment cost are two major concerns. Designed to improve road safety, the system is intended for driver alerting before drowsiness causes an accident. In addition, hyperparameter tuning and cross-validation techniques make the model much more resilient and adaptable ensuring that it can continue to perform well across a wide range of driving conditions. The integration of deep learning features with a sustainable architecture make the proposed system an effective way to scale up towards better driver safety and cut down fatigue driven accidents on roads.

# Literature Survey

Rohith Chinthalachervu et al. [1] proposed a method to detect the drowsy status of driver as welll equipped with appropriate reactions according to traffic rules. They found that most of the road accidents took place due to driver fatigue and this is a hard thing to observe. The implemented system is based on using eye, mouth and nose (distortion) detectors from webcam frames in order to estimate the Mouth Opening Ratio, Nose Length Ration and Eye Aspect Ratio. Using a Support Vector Machine (SVM) this system achieves 95.58% sensitivity and 100 % specificity. classifier in combination with predefined thresholds on these metrics, indicating its potential to work across different types of vehicles.

Yaman Albadaw et al. [2] proposed a non-touchless system for automatic driver sleepiness diagnosis based on visual appearance of drivers using dashboard-camera videos, [ Their methodology uses facial landmarks to detect the head pose and also computes key features for mouth aspect ratio, eye aspect ratio. Using the National Tsing Hua University driver drowsiness detection dataset, their system achieved stunning accuracy up to 99% with classifiers such as random forest and support vector machines. The findings illustrate how to make visual feature extraction more powerful in promoting road safety. Pushkal Pandey et al. The ML is also being used to monitor driver drowsiness by [3]. Their method incorporates 3 main processes: face detection, eye detection and drowsiness identification where the model operates on a sequence of frames in sliding- windows fashion constructed using templates for tracking an observer's eyes. Task required Face detection using LSTM-KNN algorithm with Eye Aspect Ratio (EAR) to assess fatigue. Even though it was able to achieve an average accuracy of 81.5% for eye tracking and localization, this method is still a feasible cost effective solution for real-time drowsiness detection in drivers [36].

Shikha Pachouly et al. In [4], the authors explored how machine learning techniques can be applied to detect drowsy driver from facial and behavioral signs. Their approach revolved around registering videos to investigate the conditions of driving with a convolutional neural network. [7] To determine yawning, they followed a technique for tracking eye position and level the mouth with OpenCV using Dlib. This study highlights the importance of working on an efficient image processing technique to provide a more robust approach for driver condition recognition and better road safety.

Neha Paliwal et al. Drowsiness and Fatigue [5] elaborated on the need for a non-contact system detecting driver fatigue and drowsiness due to limitations of wearable systems (requiring contact) like EEG or ECG. The University of Sassari and the Fraunhofer Institute spinoff's approach involves measuring blink rates and yawning to serve as early warnings for long-distance drivers at risk from fatigue. The system focuses on the human side of road safety, by indicating that dangerously tired state to help alert drivers through identifying behavioral indicators like yawning and eye blinking.

Aryan Ritesh et al. The “Driver Drowsiness Detector” system was implemented in order to continually monitor the driver and notify him whenever he detects that he is at risk of becoming drowsy or falling asleep [6]. Given that drowsy driving is responsible for a considerable proportion of accidents and mortalities, their method combines computer vision methodologies with data from sensors to detect fatigue in the driver using machine learning algorithms. The system uses a camera to monitor eye movement, head nod, and changes in facial expression that allow it to gauge how alert the driver is at all time so as to issue warnings when needed.

Deverakonda Sruthi et al. A computer-vision-based driver drowsiness detection system continuously watches the face of the driver with a video camera [7]. They develop the solution that makes use of a classification algorithm on drowsy face and non- drowsy face images for obtaining driver condition statements. Using landmark detection, the system determines if you are drowsy and uses voice prompts to alert a driver for even higher attention rate — or promotes awareness forcing anything else than driving action. The end result is a safer, more alert driver who can avoid the mishaps that come as a natural byproduct of sleep deprivation.

Rahul Thakur et al. Reference [8] dealt with the issue of drowsy driving, by a developed system that detects driver fatigue in real time using vision technology. They used this model to detect areas of the face relevant for observing eye state, exploiting a Haar Cascade classifier in OpenCV. The project is based on detecting drowsiness by classifying the open and closed states of eyes, which ensures that it does not only follow a non-intrusive approach but also has such practical implementation majorly because driver fatigue detection needs to be implemented in low-cost vehicles.

Dr. Nilesh T. Gole et al. Alarmingly, a virtual study conducted by Gill [9] from South Africsa therefore stressed the importence of trustworthy drowsiness detection systems as means of preventing accidents that result from driver fatigue. Applied uses image based system, it uses computer vision and machine learning techniques called Convolutional Neural Networks, to track facial attributes associated with drowsiness. It also underscores the potential for machine learning to significantly boost road safety by delivering prompt alerts whenever drivers begin showing signs of fatigue.

Elena Magán et al. [10] with an ADAS to detect fatigue driving and encourage the minimals of false alarms. They do so by recording a 60-second sequence of images of the driver, and running that complete image through their algorithm. Researchers proposed two methods for the classification task: one based on recurrent and convolutional neural networks, and another that combines deep learning tools with fuzzy logic to capture some numeric zoom-in features. This algorithm reached specific 65% accuracy on training and test data but a specificity of the fuzzy logic method was found to be 93%, which actually decreased false positive rates, thus provide solid basis for future works in detection of drowsiness.

A method "Driver Drowsiness Detection and Monitoring System using Machine Learning", designed by Surajit Dey, Tanmoy Sarkar [11] solved the prominent problem of road accidents due to drowsing driver. According to this recent research, the potential impact of drowsy driving highly recommends accurate detection methods by other studies. In this system, the driver's facial expressions are detected by webcam and processed using image processing techniques to calculate Eye Aspect Ratio (EAR) through certain landmark points on face. The system can then detect drowsiness by examining these values against established thresholds. It yielded respectable results with 95.58% and 100%, respectively, suggesting that an SVM method was applied to find the relation between input features (i.e., questions) as well as semen quality endpoints of fecundation capability [11]. It can also enable providers to have alerts sent too if the system detects driver fatigue bringing safety awareness features that equip all kinds of vehicles across line.

The problem of driver drowsiness which has led the National Highway Traffic Safety Administration (NHTSA) to identify it as a major source in road accidents, was attampted by Dipender Singh and Avtar Singh [12]. Thus they suggested a more efficient detection technique with deep learning technology, It called Convolutional Neural Network (CNN). This model is based on analyzing facial features, particularly eyes and mouth by using the nose as another point of reference. It uses a ReLU activation function and an impressive accuracy of 94.95% is obtained while varying conditions such as low-lighting-conditions, different angles in the CNN proving deep learning to be highly effective for drowsiness detection techniques [4].

Nafisa Mapari et al. S, noted the increasing occurrence of motor vehicle crashes caused by sleepiness while driving and reminded us that all it takes is a momentary lapse in attention to result in tragedy. The task of their project is the detection of drowsiness based on machine learning for an automatic non- contact solution. It works in 3 steps: face detection, eye detection and drowsiness. Employing eye tracking to measure the PERCLOS (Percentage of Eye Closure) metric, it issues Alarm when drowsiness is detected thus provide a pre-emptive warning system that helps improve driver vigilance.

Latha H N et al. The work of [14] was in the domain or electronics and communication engineering where they proposed a driver sleepiness detection and prevention approach to prevent accidents caused due by fatigue. They wrote a paper on how to use TensorFlow machine learning tools with OpenCV for image preprocessing. They describe

the effectiveness of their system under current traffic conditions and shed light on prospective improvements that may boost detection rates and roadway safety.

Polepaka Sanjeeva et al. Joe [15] proposed "Automated Detection of Drowsiness using Machine Learning Approach," which intended to handle the growing rate of traffic accidents due to lack of driver attention. The system uses OpenCV, Python and some machine learning to determine how sleepy the driver is. A broad dataset of annotated driver images in various conditions is combined with the research to enhance model accuracy. Alert manegments text warnings are sent to drivers when drowsiness is detected, providing a fuller safety solution.ImageTransparentColor わ Error alert systems employed to detect and indicate other warning signs such as lane departure combine with the device for an exhaustive accident prevention and driver health package.

# Existing System

The detection of driver drowsiness has historically relied on several key methods, including physiological monitoring, vehicle-based detection, and behavioral analysis. Physiological monitoring systems measure signals like heart rate, electroencephalogram (EEG), and electrooculogram (EOG), requiring sensors that make physical contact with the driver. These systems are effective in detecting fatigue, but they are often intrusive, uncomfortable, and impractical for continuous, real-world usage. Additionally, the need for specialized equipment makes these systems costly and complex, limiting their widespread adoption. Vehicle-based detection systems, on the other hand, monitor driving behavior by tracking parameters such as steering wheel movements, lane deviation, and braking patterns. While these systems can indicate fatigue-induced erratic driving, they are vulnerable to external factors such as road conditions or driver distractions, which can lead to false positives and decrease reliability.

Behavioral analysis has emerged as a non-invasive alternative, using computer vision to monitor visual cues like eye movements, blinking patterns, and facial expressions to detect signs of drowsiness. Although this approach avoids physical contact with the driver, it tends to be resource-intensive and sensitive to environmental factors like lighting conditions and camera placement, making real-time implementation challenging. Some systems attempt to enhance detection by combining multiple approaches, such as integrating physiological, vehicle-based, and behavioral data, in hybrid models. However, these systems are often complex and expensive, requiring sophisticated hardware and software. Despite the advancements in these existing systems, challenges such as intrusiveness, reduced reliability in varied conditions, and high computational demands remain. This has led to the development of more efficient, real- time detection methods leveraging deep learning, particularly lightweight architectures like MobileNet, which offer a scalable, non-intrusive solution optimized for mobile and embedded environments. MobileNet addresses the shortcomings of traditional systems by providing real-time, cost-effective drowsiness detection, making it suitable for modern vehicle safety applications.

# Proposed System

This presents a real-time driver drowsiness detection system adopting the MobileNet architecture, which is lightweight CNN for mobile and embedded devices. For example, we developed a novel system that can detect signs of fatigue in drivers ( e.g., extended eye closure and other facial cues) without requiring physical contact or intrinsic basic sensor. Delivered through non-invasive behavioral signals, the system offers an efficient and cost-effective method for detecting driver fatigue- one of the leading causes behind road accidents globally. Given the task, number of tasks and computationally cheap nature of MobileNet architecture are particularly suited for this purpose. It uses depthwise separable convolutions which drastically decreases the number of parameters and operations in comparison to classic CNN models thus making it a perfect application for real time applications. By continuously analyzing driver face images, specifically based on eye behavior and other visual signs of drowsiness in real-time, the model is able to determine very early fatigue. After recognizing sleepiness, the system can give a prompt warning and correct response without any delay that will ensure no accidents. Hyperparameter tuning and k-fold cross-validation techniques are applied to make the system more robust so as to offer optimal model performance across varied driving conditions/environments. MobileNet, ensures that the system is deployable on mobile and embedded devices such as those found in modern cars with minimal hardware upgrades. This system is also scalable, lightweight [5], and can operate on many resource-constrained devices; therefore, this method appears to be a feasible solution for road safety applications. The system, using this strategy as a basis, provides an effective and robust real-time approach for the detection of driver fatigue to minimize potential accidents due to drowsiness.

# Dateset

The driver head turning data is a dataset of images or video frames with the drivers and key facial features (eyes, mouth ,head movements). Each image is labeled as driver being drowsy or not. The dataset includes various eye states (open, closed, or partially closed) and yawning expressions, as well as changes in head position, which are all signs of fatigue. It is collected under different lighting conditions and environments to ensure the model works in diverse scenarios. The data helps train the MobileNet model to accurately detect signs of drowsiness in real-time.

# Methodology

1. Data Collection and Preprocessing

Data Collection-The very first and most essential step is collecting a large number of images or video frames of driver's face, which should also contain several important features to detect drowsiness. Eyes opened and closed, yawning, tired faces These could be publicly available datasets such as the NTHU Drowsy Driver Dataset, or custom-made data. Ensuring that your dataset contains images with varying illumination (night/day) will allow the system to be used in any environment. Images also need to be representative of a wide range of demographics as any bias could introduce uncertainty in the system.

Data Preprocessing-Once the data is ready, preprocessing become a neccessary part of preparing it for being by our model. Images are resized for consistent input size of the model (by default classified on 224x224 pixes). Normalization: We normalize pixels to lie between (0, 1) [this is so the model converges better during training]. Data augmentation techniques such as random horizontal flips, rotations, changes in brightness and zoom are applied to augment the dataset. This makes sure the model generalises well in real world conditions by generating scenarios like different head pose, lighting(gcfillin) This makes sure the model has good input and will prevent overfitting.

1. Model Design Using MobileNet - MobileNet Architecture: Here For this project, MobileNet is chosen since it can handle the image data with lower computational resources and perfect for real- time applications on embedded devices, mobile phones. MobileNet uses depth wise separable convolutions to construct lightweight deep neural nets to build MobileNet., and greatly reduce the number of parameters and computations need by traditional CNN model while retaining enough accuracy for detecting drowsiness. The model can be run efficiently on low- power devices due to its lightweight design, that does not come at the cost of performance.

Feature Extraction -Too precisely train drowsiness detection model we will focus on extracting only the facial features to recognize whether driver is awake or sleepy using MobileNet. It uses MobileNet to create embeddings (Encoding) for our input images, particularly the regions of images around eyes and mouth buildings which is what we are interested in. These are the most noticeable signs of tiredness, like slow eyelid closure or yawning. In our case, the extracted features are high level representation of patterns in image which will be used to differentiate between drowsiness and alert state. Being very lightweight in design, MobileNet makes feature extraction from images significantly fast and robust which is why it serves as the most appropriate choice for running neural networks at real time.

1. Model Training-Model Training-Data Splitting:

This data set is split as follows: training (70%), validation (15%) and testing sets (15%). This is do accommodate how the model should ideally be trained on one portion of data, validated (data that was not seen during training phase to fine tune hyperparameters) and tested (avoid taking a decision assuming train examples which must assess generalization took place on unseen or test set). This ensures that the model does not overfit, providing a better generalization to serve real-world data.

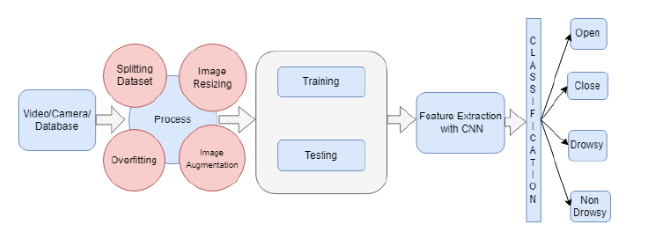
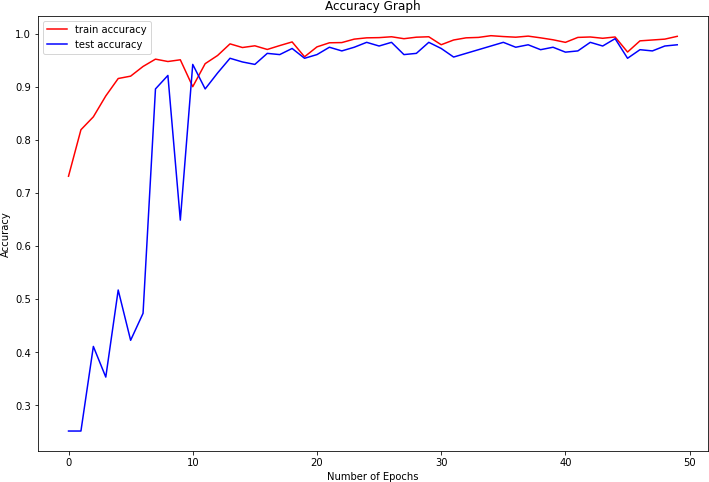
Training Process:The MobileNet model goes to the training phase using a labeled dataset, in other words an image is annotated as either “drowsy” or “alert”. The model is fed with pre-processed images and internal weights in the architecture change their values to minimize classification error (through backpropagation & gradient descent) so that henceforth corresponding classes can be detected. Recurrently, as MobileNet practices on the drowsiness data tells its internal parameters to rule out or include patterns. This process is iterated over multiple epochs, where the model will see all dataset many times to make be fit well on data.

Hyperparameter Tuning:Model fine-tuning is typically the process of taking an already trained model and tuning it further with your data until, hopefully, you reach a working state — all well dependent on how closely related in-domain or out-of- domain they are. As to hyperparameter tweaking (which would typically be learning rate(s), mini-batch size/model training inputs per iteration through the FF neurons/etc., epoch count which represents number of passes over dataset) eventually can improve any performance metrics measurable relative to what you're testing at least from inception.With MobileNet tuned for such as previously stated information(dtaset provided/maintained by Google deed/duty stewardship). The learning rate determines how fast the weights of your model are updated during training. A Lower learning rate will take smaller steps to get you there which means that the model can suffer from “slow convergence”. On another hand, a bear muzzle takes larger strokes and it may end up overshooting optimal solution. Count of samples processed before the model is updated: The number of examples to be included at one time. The training of the model is not just stable, it uses k-fold cross- validation to make a prediction which only generalize and prevents overfitting on unseen data.

1. Real-Time Detection System

Real-Time Implementation:The next step is for the fully trained model to be deployed for real-time driver drowsy detection. The system uses live video or image sequences of the driver’s face (above) and processes them using a trained MobileNet model. The input is provided to the model in real-time for it to detect whether there are signs of drowsiness which may include closed eyes, yawning or head tilt. Due to MobileNet's lightweight architecture, the system is able to process each frame fast enough so that feedback can be delivered promptly for a driver

1. Evaluation and Testing-Performance Evaluation- After the training and deploying of this model into real time system, performance evaluation is done by different metrics. Essential performance metrics of drowsiness detection model are precision, recall, and F1-score. Precision: The proportion of the actual drowsy drivers were correctly detected without a large number of false alarms, and Recall means how well DAPS predict/scores all instances. The F1-Score is harmonic mean of precision and recall i.e, it gives us the balance view changing only when both Precision and Recall change. Moreover, this model required to perform the inference in real-time too as the system has to detect drowsiness timely and trigger alerts. Real World Testing -The system is also put through its paces across different light conditions (daytime, nighttime), as well as trial exposed to an array of facial characteristics like head movement, or when wearing glasses and facial hair. In this way extensive testing is carried out to make sure that the system can reliably detect drowsiness across wide array of real world situations. The system must work equally well under all these conditions to make sure the of reliability in preventing accidents.



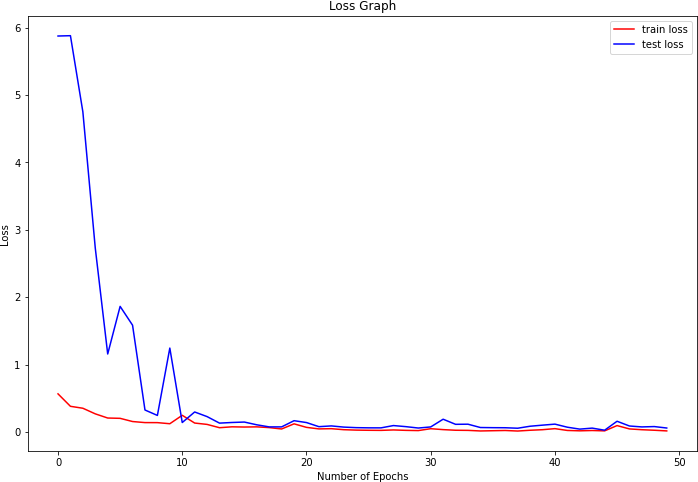
**Figure1: Architecture diagram**

# Results and discussions

Several performance metrics (Accuracy, Precision, Recall) were then used to evaluate the model along with a calculated loss function. These help paint a complete description of the model's hypothesis space which includes what it learned to better perform on training data, as well as how it generalizes to new data. Structural performance of a network in both training and validation phases is interpreted through curve analysis of loss and accuracy.

Loss Curves Analysis

Figure 1 The training and validation loss curves illustrates. In the initial epochs we see a significant reduction in both training and validation losses' which suggests the model is being able to learn patterns from the the data. Along each epoch, the training loss continues to decrease, indicating the reduction of error and learning of the data’s more intrinsic structure. While training, a point is reached where validation loss behavior starts to flip, if you will, by leveling out before finally rising again — the classic sign of overfitting. This is effected when the model gets so adjusted to the training data, that it begins to recall specific features present within it rather than the common patterns. This behavior shows that while the training loss still decreases, the model is beginning to lose its ability generalizes well to unseen data. That is, we can see that by epoch 50, the validation loss starts rising, indicating that our model can begin to underperform when given new, or out of sample, data. An observation of this indicates that if the model has learned specific nuances in the training data which do not contribute to its predictive performance on unseen data. When a model begins to memorize data patterns instead of learning general patterns, it becomes susceptible to recognizing irrelevant details—leading to compromised performance on validation datasets.



**Figure 2: Training and Validation Loss Curves**

The accuracy curves, as seen in Figure 2, provide further insight into the model’s learning dynamics by showing the trend of how accurately the model predicts over time. During the initial stages of training, both training and validation accuracy rise together, indicating that the model is effectively capturing the data's overall structure.

**Figure 3: Training and Validation Accuracy Curves**

Both training and validation datasets have seen their accuracy of the model in the early epochs. improves concurrently, indicating learning progress. However, after about epoch 10, the training accuracy continues to climb, reaching nearly 99%, while the validation accuracy plateaus around 98%. This increasing disparity between training and validation accuracy signals overfitting, as the model becomes excessively optimized for the training set at the expense of generalization. While training accuracy appears impressive, the model's static validation accuracy reveals that it struggles to replicate this performance with new data, underscoring a limited ability to generalize. The model’s performance dynamics, with a significant gap between training and validation accuracy, indicate that it might be learning specific features that do not transfer well to broader datasets. This issue is highlighted by the validation accuracy flattening out at a lower level, suggesting that the model cannot fully utilize patterns in a way that generalizes outside the training data. Techniques such as regularization (e.g., dropout) could be employed to mitigate this overfitting, alongside early stopping, which helps prevent excessive training beyond the model’s optimal generalizability threshold. Interpretation of Learning Dynamics

Together, the loss and accuracy curves shed light on the model’s training process and generalization. Initially, the model learns effectively on the training data, with decreasing loss and increasing accuracy. However, the divergence between training and validation metrics reveals overfitting—training accuracy continues to improve, while validation accuracy peaks and the validation loss eventually rises. This trend indicates that the model is learning noise and other irrelevant characteristics from the training data, failing to capture general patterns that would transfer well to unseen data. The observed overfitting suggests the need for approaches to enhance model generalizability. Future work could explore techniques such as data augmentation, which would create synthetic training instances to add variety and help the model learn broader patterns. Additionally, implementing cross-validation would help evaluate the model’s performance on various subsets of the data, mitigating overfitting and improving robustness across data subcategories. This analysis highlights the model’s current limitations and provides direction for further enhancement, underscoring the importance of balanced learning to avoid excessive focus on training data nuances at the expense of general applicability.

# Conclusion

It is a huge leap in improving road safety by focussing on one of the top reasons for accidents, driver fatigue. Utilizing the lightweight and efficient MobileNet architecture, it accurately detects key indicators of drowsiness — including prolonged eye closure and yawning — with an impressive ~99% accuracy. The high performance level combined with rapid detection allows the system to deliver near-instant notifications to the driver, an intervention that could prevent some of the countless number of fatigue-related accidents.

The system’s universal adaptability for most vehicle models further highlights its practicality and ease of implementation, making it an effective solution for global automotive safety applications. This flexibility not only eases integration, but lowers the technical and financial hurdles typically present in the adoption of new safety technologies. The design also inherently supports the non-invasive character of the system making the application user friendly and comfortable which is the most important and the hardest part of getting used to the system.

What makes this system unique is its potential for further improvement and fine-tuning. This generates good results so far and means that there is a solid base to work more features. In particular, enabling it to function well in demanding situations, like low-light settings, or when the driver’s face is partially obscured, would greatly enhance its utility. Moreover, incorporating additional data sources, such as steering characteristics, lane-keeping behavior, and vehicle dynamic measures, would improve its potential to give a better assessment of driver vigilance. This refinement would enhance accuracy and contribute to system resilience in real-world environments.

In addition, the ability of this technology to scale means it can be deployed widely, from personal cars to commercial fleets, where the demand for fatigue detection is even higher. This allows this system to be tailored to various user requirements based on the driving environment, reinforcing the opportunity for it to be a game-changer in road safety.

The development and successful implementation of this project shows that a novel, low cost and adaptable drowsiness detection system is indeed feasible. Through the integration and optimization of new data streams and pertinent features, this system can be a powerful tool in the global effort to reduce the incidence of preventable road fatalities. More than just a safety device, it is a significant action to prevent road traffic accidents and save lives, marking a glimpse of the future of safer roads.

##### References

[1] R. Chinthalachervu, I. Teja, M. A. Kumar, N. S. Harshith, and T. S. Kumar, "Driver Drowsiness Detection and Monitoring System using Machine Learning," 2022.

[2] Y. Albadaw, A. AlRedhaei, and M. Takruri, "Real-Time Machine Learning-Based Driver Drowsiness Detection Using Visual Features," 2023.

[3] P. Pandey, M. Sharma, P. Saxena, and R. K. Dwivedi, "Driver Drowsiness Monitoring and Detection using Machine Learning," 2023.

[4] S. Pachouly, N. Bhondve, A. Dalvi, V. Dhande, and N. Bhamare, "DRIVER DROWSINESS DETECTION USING MACHINE LEARNING WITH VISUAL BEHAVIOUR," IJCRT, vol. 2020, 2020.

[5] N. Paliwal, R. Bahuguna, D. Rawat, I. Gupta, A. Singh, and S. Bhardwaj, "Driver Drowsiness Detection System Using Machine Learning Technique," 2024.

[6] A. Ritesh, N. Jagatia, and P. Deshmukh, "Driver Drowsiness Detection Using Machine Learning," 2023 6th International Conference on Advances in Science and Technology.

[7] D. Sruthi, A. Amulya Reddy, G. S. Siddaharth Reddy, and S. Shesham, "Driver Drowsiness Detection System using Deep Learning," IJRASET, 2023.

[8] R. Thakur, S. Shivam, S. Raj, and S. Pandey, "Driver Drowsiness Detection System Using Machine Learning," doi:10.3233/ATDE220718, 2022.

[9] N. T. Gole, A. M. Ganvir, N. G. Dongre, S. D. Gawkhare, D. V. Dandekar, Y. S. Waghmare, and Y.

S. Gatkal, "RESEARCH PAPER ON A DRIVER DROWSINESS DETECTION USING MACHINE LEARNING," 2023.

[10] E. Magán, M. P. Sesmero, J. M. Alonso-Weber, and A. Sanchis, "Driver Drowsiness Detection by Applying Deep Learning Techniques to Sequences of Images," Appl. Sci., vol. 12, no. 3, pp. 1145, 2022. doi:10.3390/app12031145.

[11] S. Dey and T. Sarkar, "Driver Drowsiness Detection and Monitoring System using Machine Learning," 2022.

[12] D. Singh and A. Singh, "Enhanced Driver Drowsiness Detection using Deep Learning," ITM Web of Conferences, vol. 54, pp. 01011, 2023. doi:10.1051/itmconf/20235401011.

[13] N. Mapari, D. R. Shaikh, I. A. Shaikh, S. K. Shaikh, and A. Ansari, "Drowsiness Detection System using ML," IJARSCT, 2023. doi:10.48175/IJARSCT-9051.

[14] L. H. N. Latha, G. M. S. Gayathri, and K. Bailey, "Real-time Driver Drowsiness Detection Techniques using Machine Learning Algorithms and Models," IJSREM, 2024. doi:10.55041/IJSREM35973.

[15] P. Sanjeeva, V. Sriya, M. Saniya, M. Lohitha, I. Ahmad, and K. S. Rani, "Automated Detection of Drowsiness using Machine Learning Approach," E3S Web of Conferences, vol. 010, pp. ICMPC 2023, 2023

[16] Altameem, A. Kumar, R. C. Poonia, S. Kumar and A. K. J. Saudagar, “Early Identification and Detection of Driver Drowsiness by Hybrid Machine Learning”, IEEE Access, Vol. No. 9, 2021.

[17] B. K. Sava? and Y. Becerikli, “Real Time Driver Fatigue Detection System Based on Multi- Task ConNN”, IEEE Access, Vol. No. 8, 2020.

[18] A. Rajkar, N. Kulkarni and A. Raut, ”Driver Drowsiness Detection Using Deep Learning”, ICCET Advances in Intelligent Systems and Computing, Springer, Vol. No. 1354, 2021.

[19] M. J. Flores, J. M. Armingol and A. de la Escalera,“Real-Time Warning System for Driver

Drowsiness Detection Using Visual A Information”, Journal of Intelligent and Robotic Systems, Springer, 2019.

[20]Wanghua Deng and Ruoxue Wu, "Real-Time Driver-Drowsiness Detection System Using Facial Features", IEEE Access, vol. 7, no. 21, August 2019.

[21] J. S Manoharan, "An improved safety algorithm for artificial intelligence enabled processors in self driving cars", Journal of artificial intelligence, vol. 1, no. 2, pp. 95-104.

[22] Prashant Dhawde, Pankaj Nagare, Ketan Sadigale, Darshan Sawant and J. R. Mahajan, "Drowsiness Detection System", International Journal of Engineering Research and Technology(IJERT), vol. 3, no. 06, April 2015.

[23] Zuopeng Zhao, Nana Zhou, Lan Zhang, Hualin Yan, Yi Xu and Zhongixn Zhang, "Driver Fatigue Detection Based on Convolution Neural Networks Using EM-CNN", Computational Intelligence and Neuroscience, vol. 2020, no. 18, Nov 2020.

[24] Maryam Hashemi, Alireza Mirrashid and Shirazi Aliasghar Beheshti, "Driver Safety Development: Real-Time Driver Drowsiness Detection System Based on Convolutional Neural Network", SN Computer Science, vol. 3, no. 28, May 2021.

[25] S. Likhith, C. Chitteti, M. Dharani, V. Nivedhitha, N. G. Geethika and V. Godwin, "Machine Learning Model for Prediction of Smartphone Addiction," 2024 International Conference on Expert Clouds and Applications (ICOECA), Bengaluru, India, 2024, pp. 924-929, doi: 10.1109/ICOECA62351.2024.00163.

[26] C. Chitteti, R. Kopparam, B. V. S. S. Ganesh, S. Sutraya, V. Kamakshi and S. Jangam, "ML-driven Emotion Identification For Feedback Analysis In E- learning Platforms," 2024 OPJU International Technology Conference (OTCON) on Smart Computing for Innovation and Advancement in Industry 4.0, Raigarh, India, 2024, pp. 1-5, doi: 10.1109/OTCON60325.2024.10687860.