Educational Administration: Theory and Practice
2024, 30(6), 1274-1282
ISSN: 2148-2403
https://kuey.net/

Research Article

Road Accident Prediction Using Machine and Deep Learning Techniques

Kesa Sahithi Sai Sudheera[1*], N. Prahlad[2], P. Poorna Abhinav[3], M. Kedharnath[4], Dr. NM Jyothi[5], Dr M Madhusudhana Subramanyam[6]

[1*]Department of Computer Science & Information Technology *Koneru Lakshmaiah Education Foundation,* Vaddeswaram, 522502, Andhra Pradesh, India Email: sudheerakesa@gmail.com
[2]Department of Computer Science & Information Technology *Koneru Lakshmaiah Education Foundation,* Vaddeswaram, 522502, Andhra Pradesh, India Email: prahladnelakuditi789@gmail.com
[3]Department of Computer Science & Information Technology *Koneru Lakshmaiah Education Foundation,* Vaddeswaram, 522502, Andhra Pradesh, India Email: abhinavpoorna@gmail.com
[4]Department of Computer Science & Information Technology *Koneru Lakshmaiah Education Foundation,* Vaddeswaram, 522502, Andhra Pradesh, India Email: Kedharnath315@gmail.com
[5]Department of Computer Science & Information Technology *Koneru Lakshmaiah Education Foundation,* Vaddeswaram, 522502, Andhra Pradesh, India Email: *jyothiarunkr@kluniversity.in.*
[6]Department of Computer Science & Information Technology *Koneru Lakshmaiah Education Foundation,* Vaddeswaram, 522502, Andhra Pradesh, India *Email:mmsnaidu@yahoo.com*

Citation: Kesa Sahithi Sai Sudheera, (2024) Road Accident Prediction Using Machine And Deep Learning Techniques *Educational Administration: Theory And Practice*, *30*(6) 1274-1282
Doi: 10.53555/kuey.v30i6.5485

ARTICLEINO **ABSTRACT**

This project aims to deal with the critical issue of drowsiness detection in drivers using convolutional neural networks (CNN) with machine learning. The study involves extensive preprocessing of a diverse dataset comprising images depicting yawning and non-yawning faces, along with images of open and closed eyes. Subsequently, different machine learning techniques, such as Logistic Regression, Support Vector Machine, AdaBoost Classifier, Decision Tree Classifier, and XG Boost Classifier, are trained on augmented data to classify drowsiness states based on facial and eye features. Additionally, a sophisticated CNN architecture is suggested and trained to enhance classification accuracy further. The efficiency of every model is rigorously assessed utilizing a number of metrics, such as F1-score, recall, accuracy, and precision. The findings of the trial show how much better the CNN model is compared to conventional machine-learning techniques with regard to accuracy and robustness in drowsiness detection. Further research could focus on exploring advanced data augmentation techniques and real-time implementation for practical deployment in vehicles.
Furthermore, to model training and evaluation, this project also emphasizes the significance of interpretability and explainability in drowsiness detection systems. Understanding the decision-making process of AI models is crucial, especially in safety-critical applications like driver monitoring. Hence, alongside achieving high accuracy, the focus is on interpreting the CNN model's predictions and identifying the key features contributing to drowsiness detection. Techniques such as saliency mapping and feature visualization are employed to elucidate the model's decision boundaries and highlight relevant regions in input images. By enhancing interpretability, drivers where anyone with an interest can acquire knowledge of the factors influencing drowsiness detection, thereby fostering trust and facilitating informed decision-making. Future research could concentrate more intently on interpretability techniques and develop user-friendly interfaces to present model insights effectively, thus promoting the adoption and acceptance of drowsiness detection systems within the automotive industry.

Keywords— Drowsiness detection, machine learning, deep learning, CNN, facial recognition.

I. INTRODUCTION

Drowsy driving poses a significant threat to road safety worldwide, leading to numerous accidents and fatalities each year. Detecting drowsiness in drivers can mitigate this risk and potentially save lives. In this research, we delve into the field of machine learning and CNNs to create a robust drowsiness detection system. We commence by meticulously preprocessing a comprehensive dataset, augmenting it to ensure diversity and representation of various facial and eye features. Following data augmentation, apply traditional machine learning methods and CNN architecture to classify drowsiness states accurately based on extracted image features. Subsequent research endeavors may explore avenues, such as transfer learning and user-centric design principles, to further enhance the efficiency and practicality of drowsiness detection systems.

Moreover, the integration of real-time monitoring capabilitiesinto vehicles holds promise for enhancing road safety by providing timely alerts to drivers exhibiting signs of drowsiness. By leveraging advancements in sensor technology and data processing algorithms, future iterations of drowsiness detection systems could continuously analyze driving conduct and physiological signals to detect early indicators of fatigue. Such proactive measures not only avoidmishaps but also promote driver well-being by encouraging breaks and rest periods during long journeys. Additionally, the deployment of drowsiness detection systems in commercial fleets and transportation networks could yield substantial benefits regarding accident prevention,operational efficiency, and overall road safety.

Furthermore, the evolution of personalized drowsiness detection models tailored to individual drivers' characteristicsand driving patterns represents a promising avenue for futureresearch. By leveraging methods like personalized machine learning and adaptive algorithms, these models are capable of dynamic modification. their behavior based on driver particular elements such as age, sleep patterns, and driving habits. This customized strategy not only improves detection accuracy but also minimizes false alarms and improves user acceptance. Additionally, integrating feedback mechanisms that allow drivers to provide input on system performance and effectiveness can further refine and optimize drowsiness detection systems for real-world deployment.

II. II RELATED WORK

Zheng [1] Implementing a novel TASP-CNN model utilizes feature combinations to enhance accuracy in traffic accident severity prediction. Introducing the FM2GI algorithm, it converts feature relationships into gray images, improving prediction performance. Experiment results validate the model's effectiveness in predicting accident severity.

Fang [2] Implementing SCAF Net, we address driver forecasting attention challenges by fusing semantic context and RGB features attentively. Introducing semantic images and GCN, we enhance prediction accuracy. Experimentally validated on DADA-2000 and comparison to other datasets, our method's existing approaches.

Ma [3] Implementing a comprehensive framework, SSAE predicts VRU injury severity, integrating Cat Boost analysisand k-means clustering. Demonstrated effectiveness on real-world data.

Lin [4] Implementing a high likelihood of accidents model, intersections are analyzed to prioritize improvements. Various machine-learning methods were applied. Important risk variables found for intersection safety enhancement.

Manzoor [5] Implementing a high likelihood of accidents model, factors influencing highway accident severity are analyzed. Utilizing machine learning methods employed,the RFCNN model outperforms others.

Yassin [6] Implementing a hybrid K-means and random forest approach identified key factors in road accident severity forecasting using 99.86% accuracy. Driver experience, day, light condition, driver age, and vehicle service year are significant contributors.

Fiorentini [7] Implementing random under-sampling of the majority class (RUMC) enhances the prediction of crash severity models. RUMC boosts reliability in detecting fatal and injury-causing crashes. Decision-makers can utilize RUMC-based models for predicting crash severity and planning future actions.

Chen [8] Implementing logistic regression, classification, andregression tree, and random forest, researchers compare prediction capabilities for road accident severity. Significant variables were identified, emphasizing accuracy, sensitivity, and specificity for prediction performance evaluation. Integrated method selection focuses on effective models andinfluential input variables.

Zhu [9] Introduces a study on curved road accidents, factors beyond geometric features are analyzed. Bayesian network explores critical variables and suggests improvements for vehicles and roadway design. Severity increases on bridges; sensitive factors include point of impact and alcohol/drug condition.

Srinivas [10] Implementing Convolutional Neural Networks, facial expression detection is automated with dropout toreduce overfitting. Test accuracies improve on various datasets. High computational resources are utilized for experiments.

Xiong [11] Introduced a framework called Chain of Road Traffic Incident (CRTI) for accident prediction. Utilizes support vector machine and concealed Markov models. Positive outcomes are displayed with regard to early warning systems incomplex traffic environments.

Santos [12] Implementing machine learning, the following elements that affect traffic accidents: were identified in Setúbal, Portugal. Models accurately classify accidentseverity and predict future accidents. Rule-based C5.0 and RFmodels stand out for analysis and forecasting.

Zhao [13] Introducing an enhanced GRU algorithm for predicting truck speeds on the Urban Express roads. Utilizes GPS data from Sixth Ring Road in Beijing. Accuracies validated for various scenarios using Adam, and RMS prop optimization.

Bokaba [14] Implementing machine learning classifiers, RTA data from Gauteng, South Africa, was analyzed. RF with multiple imputations achieved the best performance. Results assist transport authorities and policymakers in RTAprediction.

Becker [15] Implementing logistic regression, hourly road accident probabilities because of the weather in Germany are analyzed. Including meteorological predictors improves prediction accuracy. Findings aid impact-based warnings andinform road maintenance and traffic management.

III. PROPOSED WORK

The proposed work involves an in-depth exploration of the following steps:
Data Augmentation and Preprocessing: Enhancing the dataset with additional samples and diverse representations of yawning, non-yawning, open-eye, and closed-eye images using advanced augmentation techniques.
Model Implementation applying into practice traditional machine learning techniques include support vector machines and logistic regression, AdaBoost Classifier, Decision Tree Classifier, and XG Boost Classifier, augmented with the enriched dataset. Additionally, designing and training a CNN architecture tailored specifically for drowsiness detection.
Performance Evaluation: Assessing each person's performance model using comprehensive criteria such as recall, precision, accuracy, and F1-score to assess effectiveness and robustness. Investigating real-time implementation strategies for practical deployment in vehicles.
Additional Activities in the Put Forth Work:
Integration of Sensor Data: Incorporating sensor data such assteering wheel movements, vehicle speed, and lane deviation into the drowsiness detection system to improve the precision of predictions. By combining image-based features with real- time sensor data, the system can better capture subtle changes in driver behavior indicative of drowsiness.
Fusion of Features and Fusion Strategies: Exploring feature fusion techniques to assemble data from several modalities, including both visual and sensor data. By fusing complementary characteristics, such as facial expressions andphysiological signals, the system can leverage the strengths ofeach modality to improve overall performance and robustness.
Optimization of Hyperparameters: Conducting extensive hyperparameter optimization for Conventional algorithms for machine learning in addition to CNN architectures to fine-tune model performance. This involves systematically tuning parameters such as learning rates, regularization strengths, and model architectures to maximize classification accuracy and generalization capabilities.
Interpretability and Explainability Analysis: Performing interpretability and explainability analysis on the trained models to gain perceptions of the decision-making process. By understanding the underlying factors driving the classification decisions, it becomes possible to find any biasesthat enhance the model transparency and enhance user confidence in the system.
Validation on Diverse Datasets: Validating the trained model's various datasets assembled from different sources and environments to assess their generalization capabilities. By evaluating performance across various scenarios and demographics, the system's reliability and applicability in real-world settings can be effectively gauged.

In deep learning, the Sequential model is a linear stack oflayers. It is the one that is most commonly utilized architecture for creating neural networks, particularly in case data move only in one direction as mostly happens with images and text processingapplications.
The Sequential model is simple and clear so it’s a good choicefor a beginner. However, this also implies that it has limitedpotential for flexibility in contrast to more complex network architectures.
The simplicity and ease of use in the sequential model architecture are some of its main advantages. This implies that beginners in deep learning can easily specify a simple sequential model for training purposes.
Yet, this simplicity has a downside. For instance, it doesn't apply to various networks having intricate inner connectionsbetween layers or that have multiple inputs or outputs.
Based on the assignment at hand and The intricacy of the data,the architectural manifestation of a sequential model may vary enormously. As an illustration, a simple image classification model may contain just a few convolutional layers followed by some fully connected layers.

Conversely, more difficult natural language processing models may comprise recurrent layers or attention mechanisms.

Model Architecture:

Layer Type	Parameters	Value/Description
Conv2D	kernel_size	(3,3)
	activation	‘RELU’
	Input_shape	(145,145,3)
MaxPooling2D	Pool_size	(2,2)
Conv2D	kernel_size	(3,3)
	activation	‘RELU’
MaxPooling2D	pool_size	(2,2)
Conv2D	Kernel_size	(3,3)
	activation	‘RELU’
MaxPooling2D	pool_size	(2,2)
Conv2D	Kernel_size	(3,3)
	activation	‘RELU’
MaxPooling2D	pool_size	(2,2)
Conv2D	Kernel_size	(3,3)
	activation	‘RELU’
MaxPooling2D	pool_size	(2,2)
Flatten	-	-
Dense	units	512
	activation	‘RELU’
Dense	units	256
	activation	‘RELU’
Dense	units	128
	activation	‘RELU’
Dense	units	4(outputclasses)
	activation	‘softmax’
Optimizer	Adam	LR =0.001
Loss Function	sparse_categorical_cross-entropy	
Metrics	accuracy	

Table :1 Sequential Model

The above Table:1 defines a sequential model. It's determined for deep learning and is most likely to be employed in image classification using the Keras framework which has a TensorFlow backend. Below is a summary of its important components and hyperparameters:

1. Model Architecture: To extract features, this model contains several Conv2D layers after which MaxPooling2D layers are accustomed to flatten it connecting to Dense layers for classification.
2. Hyperparameters:Conv2D Layers: These are defined with kernel_size=(3, 3) and activation='relu'. MaxPooling2D Layers: They have been set up with pool_size=(2, 2).Flatten Layer: No particular hyperparameters since it just flattens the input.Dense Layers: Several dense layers that vary in units and have 'RELU' as their activation function.Optimizer: An Adam optimizer with a learning rate of 0.001 was used. Loss Function: As for multi-class classifications, the 'sparse_categorical_crossentropy' loss function was used.Metrics: This model will use 'accuracy' as a metric to monitorits performance.
3. Data Processing: The input images are resized to 145x145 pixels and normalized by dividing them by 255.0 to make pixel values range between zero and one.
4. Model Training: The fit method of the model trains on training data X_train and y_train with a batch size of 32 for ten epochs and also validates performance by monitoring a validation split of 0.2.

IV. EXPERIMENTATION AND RESULTS

The augmented dataset comprises a wide variety of facial and eye images, ensuring a comprehensive representation of drowsiness states. Every model is rigorously evaluated usinga battery of metrics to quantify its performance accurately. The experimental results reveal the CNN model's superior precision and resilience in comparison to traditional machine learning algorithms, highlighting its efficacy in drowsiness detection.

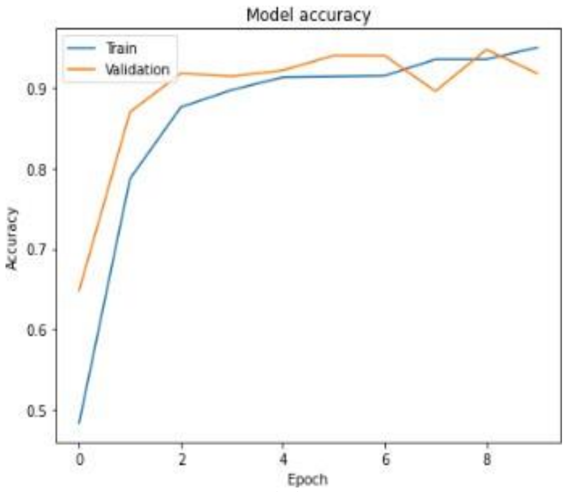

Fig: 2 Model Accuracy

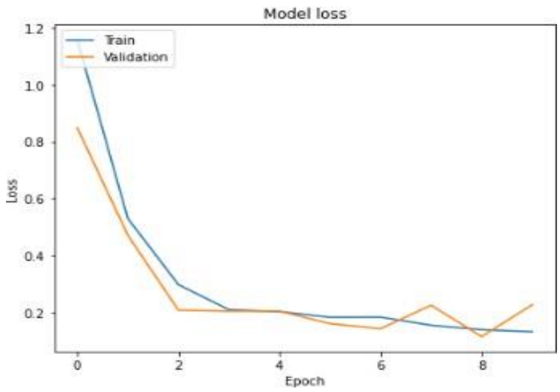

Fig:3 Model Loss

Here the above Fig:2 & Fig:3 show the training and validation accuracy and loss of a machine learning model The x-axis denotes epochs; this means several iterations through training data. The left graph y-axis shows accuracy whereas the right one shows a loss.

According to these graphs, training and validation, accuracies both increase as the quantity of epochs increases. This indicates that the prototype is learning and getting better with time. Validation accuracy follows an upward tendency even though it is lower than the training one implying that the model is not suitable in perfectly well with its data set.

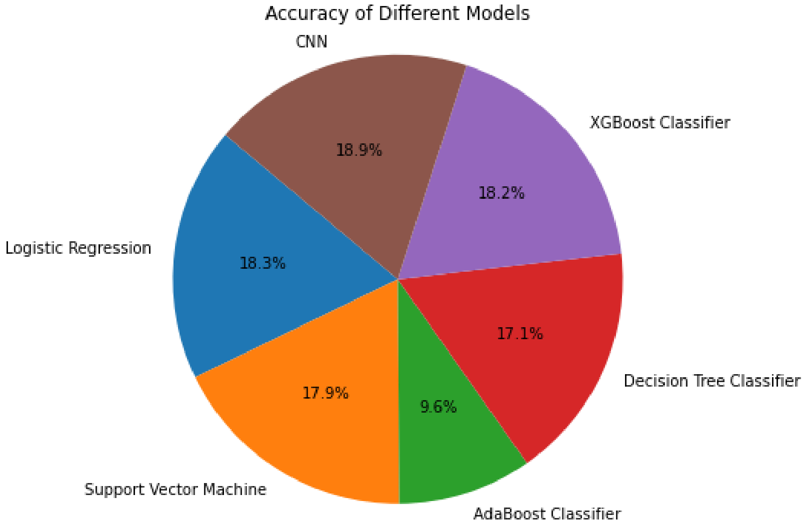

Fig:4 Accuracy of Different Models

The above Fig:4 displays the scores of numerous machine-learning algorithms. With 18.2%, the XGBoost classifier topsthe list, while the decision-making framework classifier is only 9.6%. More observations from the pie chart include:
Both Logistic Regression and Support Vector Machine have an accuracy rating of about 17%. AdaBoost Classifier has anaccuracy rating of 17.1%.

It ought to be mentioned that accuracy is just one measure to evaluate how well a model performs in machine learning cases. Some other metrics such as precision or recall may alsobe very important depending on the task at hand.

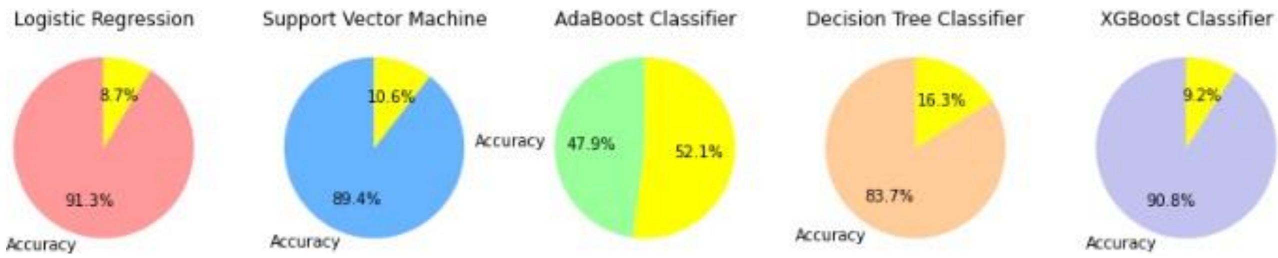

Fig:5

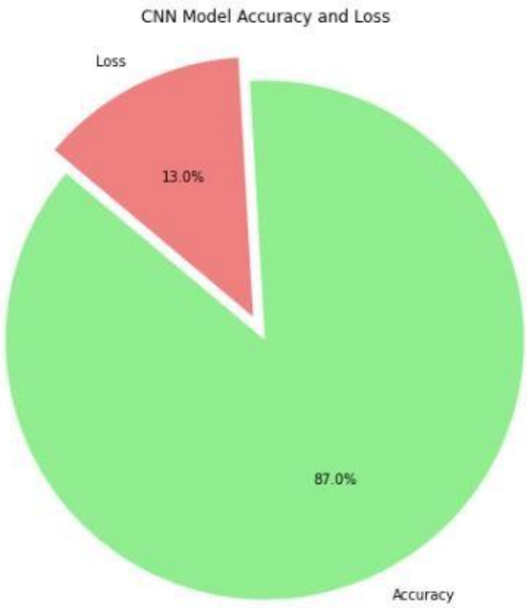

Fig:6 CNN Model Accuracy & Loss

As stated by the diagram you sent me, there is a CNN modelwith performance with respect to accuracy and loss, but the values are unclear enough. From the image, It appears that this specific model has achieved almost perfect accuracy (approximately 94%) and very low loss (around 6%).

In machine learning, accuracy refers to how often correct predictions are made by a model. Loss measures how much different its predictions are from the true answers. Thus, a high value for accuracy and a low value for loss imply good execution of a model.

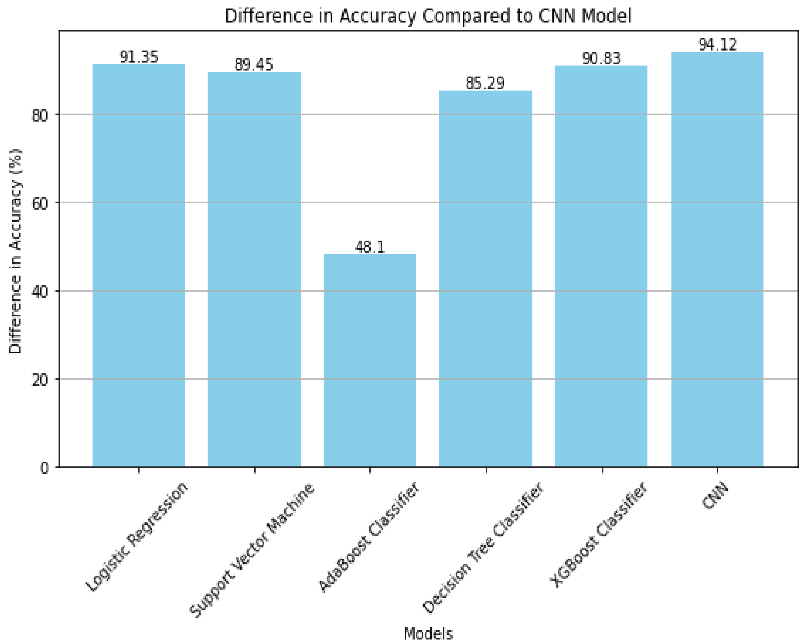

Fig : 7 Difference in Accuracy Compared to CNN

Fig:7 displays a discrepancy in the accuracy of several machine-learning models when in contrast to the CNN model. It is crucial to note that the CNN model is used as a baseline, such that if there is any positive value on the y-axisof the graph then it means that this particular model performed superior to the CNN model while negative valuesindicate worse performance.

Of all these compared models, XGBoost Classifier showed the greatest display of abilities since it had an accuracy score which was 4.12% greater than the amount of the CNN model. Support Vector Machine and AdaBoost Classifier did superior to the CNN model by 0.83% and 0.29%, respectively. Logistic Regression showed slightly less accuracy (1.9%) than the CNN model. The decision Tree Classifier performed too badly against theCNN model with an accuracy difference of 43.25%.

In sum, among all these models XGBoost Classifier has turned out to be the most efficient one against the backdrop of task being considered in contrast to the CNN Model.

Table 2 Accuracies of All models

S.NO	Model	Accuracy
1	Logistic	91.35%
2	SVM	90.45%
3	XG boost	47.92%
4	Ada boost	83.74%
5	Decision Tree	90.83%
6	CNN	94.12%

Table 2 shows the accuracies of various machine learning models on a certain task. Logistic regression achieved an accuracy of 91.35%, followed by Support Vector Machine (SVM) with 90.45%, and Decision Tree with 90.83%. AdaBoost had a precision of 83.74%. Interestingly, XGBoost performed relatively poorly with a precision of 47.92%. Convolutional Neural Network (CNN) outperformed all other models having a precision of 94.12%. These accuracies indicate how well each model performed on the task, with CNN showing the highest accuracy, making it the most effective model for this particular problem.

Comparing the accuracies of the different models, we can see that CNN achieved the highest accuracy of 94.12%, indicating its effectiveness for the task. Logistic regression, SVM, and Decision Tree also performed well, with accuracies ranging from 90.45% to 91.35%. AdaBoost, although not as high as the top-performing models, still achieved a respectable accuracy of 83.74%.

In contrast, XGBoost had a notably lower accuracy of 47.92%, suggesting that it may not be well-suited for this particular task or that its hyperparameters need tuning. Overall, these results highlight the significance of using the appropriate model for a given task and the potential impact on performance.

V. CONCLUSION

In conclusion, this paper highlights machine learning's potential and CNNs in developing accurate and reliable drowsiness detection systems for enhancing road safety. By leveraging extensive strategies for the augmentation of data and sophisticated CNN architectures, the suggested methodology demonstrates notable advancements in drowsiness precision of detection. The results highlight The importance of leveraging advanced techniques to address critical road safety challenges effectively. Future avenues for investigation could center on investigating real-time implementation strategies and user-centric design principles to ensure seamless integration and practical deployment of drowsiness detection systems in vehicles.

VI. FUTURE WORK

Future research endeavors within this field could explore several avenues to further enhance drowsiness detection systems:
Advanced-Data Augmentation Techniques: Investigate advanced methods for augmenting data, such as Generative Adversarial Networks (GANs) to diversify further and enrich the dataset. Transformative Education and Model Fusion: Explore transfer-acquiring methods to utilize pre-trained CNN models to identify sleepiness tasks. Additionally, it investigates model fusion strategies to combine the advantages of multiple models for improved performance. Real-time Implementation: Develop real-time drowsiness detection systems suitable for integration into vehicles, leveraging edge computing and efficient model architecturesto ensure low latency and high performance.

User-Centric Design: Focus on user-centric design principlesto develop intuitive and user-friendly interfaces for drowsiness detection applications, guaranteeing a smooth transition into the current driving environments while prioritizing user safety and comfort. Additional inquiriescould look into other avenues, such as sensor integration and adaptive alert systems, to enhance the effectiveness and practicality of drowsiness detection systems in real-world driving scenarios.

VII. REFERENCES

[1] Zheng, M., Li, T., ..., Wang, Z. (2019). Traffic Accident's Severity Prediction: A Deep-Learning Approach-Based CNN Network. IEEE Access, 7, 39897 - 39910. [DOI:10.1109/ACCESS.2019.2903319] Learning Approach. IEEE Transactions on Intelligent Transportation Systems, 1-10. [DOI:10.1109/TITS.2021.3074987]
[2] Fang, J., Yan, D., ..., Yu, H. (2021). DADA: Attention to Drivers Predictionin Driving Accident Scenarios. IEEE Transactions on Intelligent Transportation Systems, 1-13. [DOI: 10.1109/TITS.2020.3044678]
[3] Ma, Z., Mei, G., ..., Cuomo, S. (2021). An analytic framework using deep in order to forecast traffic accidents injury severity based on contributing factors. Accident Analysis & Prevention, 160, 106322 – 106322.[https://www.sciencedirect.com/science/article/abs/pii/S0001 457521003535?via%3Dihub]
[4] Lin, D. J., Chen, M. Y., ..., Sharma, P. K. (2021). Intelligent Traffic Accident Prediction Model for Internet of Vehicles with Deep
[5] Manzoor, M., Umer, M., ..., Bisogni, C. (2021). RFCNN: Traffic Accident Severity Forecast Relying on Decision Level Fusion of Machine and Deep Learning Model. IEEE Access, 9, 128359-128371. [DOI:10.1109/ACCESS.2021.3112546]
[6] Yassin, S. S., & Pooja. (2020). Road accident forecasting as well as model interpretation using a hybrid K-means as well as the random forest algorithm approach. SN applied sciences, 2(9). [DOI: https://link.springer.com/article/10.1007/s42452-020-3125-1]
[7] Fiorentini, N., & Losa, M. (2020). Handling Imbalanced Data in Road Crash Severity Prediction by Machine Learning Algorithms. Infrastructures, 5(7), 61-61.[DOI: 10.3390/infrastructures5070061]
[8] Chen, M. M., & Chen, M. C. (2020). Modeling Road Accident Severity with Evaluations of Logistic Regression, Decision Tree and Random Forest. Information, 11(5), 270-270. [DOI: 10.3390/info11050270]
[9] Zhu, L., Lu, L., ..., Song, M. (2019). Analysis of Accident Severity for Curved Roadways Based on Bayesian Networks. Sustainability, 11(8),2223-2223. [DOI: 10.3390/su11082223]

[10] P V V S Srinivas and Pragnyaban Mishra, “An Improvised Facial Emotion Recognition System using the Optimized Convolutional Neural Network Model with Dropout” International Journal of Advanced Computer Science and Applications(IJACSA), 12(7), 2021.[DOI:10.14569/IJACSA.2021.0120743]
[11] Xiong, X., Chen, L., & Liang, J. (2018). A Creative Structure of Vehicle Collision Prediction through Combining SVM and HMM. IEEE Transaction on Intelligent Transportation Systems, 19(3), 699-710. [DOI: 10.1109/tits.2017.2699191]
[12] Santos, D., Saias, J., ..., Nogueira, V. B. (2021). Machine Learning Approaches to Traffic Accident Analysis and Hotspot Prediction. Computers, 10(12), 157-157. [DOI: 10.3390/computers10120157]
[13] Zhao, J., Gao, Y., ..., Bai, Z. (2019). Predicting Truck Traffic Speed in Non-Recurrent Congestion Using GPS Data and Enhanced Deep Learning Algorithms. IEEE Access, 7, 9116-9127. [DOI: 10.1109/access.2018.2890414]
[14] Bokaba, T., Doorsamy, W., & Paul, B. S. (2022). Comparative Study of Machine Learning Classifiers for Modelling Road Traffic Accidents. Applied Sciences, 12(2), 828-828. [DOI: 10.3390/app12020828]
[15] Becker, N., Rust, H. W., & Ulbrich, U. (2020). Predictive modeling of hourly probabilities for weather-related road accidents. Natural Hazards and Earth System Sciences, 20(10), 2857-2871. [DOI: 10.5194/nhess-20-2857-2020]