A Novel Deep Learning-Assisted Truck Driver Drowsiness Record using Blockchain Technology

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***Abstract*—This study introduces an innovative approach involving Deep Learning-Assisted Truck Driver Drowsiness Record using Blockchain Technology. It surpasses previous research by not only classifying driver drowsiness through deep learning techniques but also implementing blockchain technology for secure data management. Focusing on trucks in logistics, the research presents a hybrid system that combines deep learning and blockchain to classify and securely record instances of driver drowsiness, thereby providing timely warnings to prevent accidents. The blockchain's immutable and tamper-resistant nature ensures the credibility of recorded data. This system enables truck drivers to access their drowsiness records via mobile devices, allows logistic companies to evaluate driver performance, and permits insurance companies to adjust premiums based on drowsiness occurrences. The research evaluates three deep learning algorithms (VGG-16, MobileNet, CNN) achieving 50% accuracy each on a grayscale image driver drowsiness dataset. Additionally, smart contracts are employed for the blockchain storage of drowsiness records.**

***Index Terms*—Deep Learning , Driver Drowsiness, Blockchain record, truck.**

I. INTRODUCTION

Driver drowsiness detection is a critical safety feature in modern vehicles aimed at reducing accidents caused by drowsy or fatigued drivers. Fatigue can impair a driver's ability to concentrate, slow reaction times, and affect decision-making, making it a major concern on the roads [1]. The main objective of drowsiness detection systems is to monitor the driver's behavior and physiological signals to identify signs of drowsiness or inattention. These systems can alert the driver or trigger other safety measures to prevent accidents [2].

There are various methods and technologies used in driver drowsiness detection systems, these include:

Computer Vision Approach: A method widely used for detecting driver drowsiness employs computer vision through cameras installed within the vehicle. These cameras monitor the driver's facial features, including eye movement, blink rate, and head position. The analysis of these parameters offers valuable insights into the driver's level of attention and can identify signs of drowsiness, such as frequent blinking or drooping eyelids. By referencing research [3], this approach provides a non-intrusive means of gauging driver alertness.

Behavior Analysis through Steering: Another technique involves observing the driver's steering behavior to identify changes that might indicate drowsiness. This system focuses on alterations in driving patterns, such as increased steering irregularities or reduced smoothness. These shifts in behavior could be indicative of driver fatigue. This approach, discussed in [3], presents an innovative way to detect drowsiness by analyzing real-time steering dynamics.

Lane Departure Warning and Biometric Sensors: Monitoring the vehicle's position within a lane is yet another approach for detecting drowsiness. By tracking potential unintentional lane departures, which could occur due to drowsiness or distraction, these systems offer an effective means of alerting the driver. Additionally, more advanced systems employ biometric sensors that measure physiological signals like heart rate and skin conductance. These sensors detect changes that reflect the driver's stress levels and fatigue, as highlighted in [3].

Machine Learning and Safety Measures: Machine learning algorithms play a crucial role in various drowsiness detection systems. These algorithms analyze data collected from different sensors and learn patterns associated with drowsiness. As a result, they continuously adapt and enhance their accuracy over time, contributing to their efficacy [4]. When signs of drowsiness are detected, the system can issue warnings using visual or audible cues, like sounds or dashboard messages. Some systems might also activate safety features, such as adaptive cruise control or emergency braking, to mitigate potential accidents.

Enhancing Road Safety and Limitations: The implementation of driver drowsiness detection technology holds the promise of significantly improving road safety by preventing accidents attributed to driver fatigue. However, it's important to acknowledge that these systems aren't infallible. Drivers must still prioritize proper rest and take breaks during long journeys to minimize the risk of drowsy driving, as underscored by research [4].

Motivation: Prior studies did not effectively address the challenges linked to the utilization of a centralized Internet of Things (IoT) server for data storage. One of the prominent issues is the storage of data in a central device, computer or cloud which is prone to data modification or loss. The earlier research approaches did not adequately tackle the problem of data mutability. This mutability implies that the stored data was susceptible to unauthorized alterations or modifications, potentially enabling malicious entities to tamper with the data stored on the server.

In essence, the lack of comprehensive solutions in prior research rendered the central storage systems such as IoT server, vehicle blackbox susceptible to data manipulation. The concentration of data within a single server made it an appealing target for data mutability, with potential consequences extending to the entire system's integrity and functionality. The limited attention to sensitive data mutability issues further exacerbated the trust concerns. If the stored data could be altered without proper oversight or safeguards, it significantly undermined the trustworthiness and accuracy of the information stored within the system.

These deficiencies underscore the need for a more robust and secure approach to IoT data storage. A more effective solution should encompass strategies that distribute data storage, reducing the risk associated with a single point of attack. Moreover, measures should be in place to ensure the immutability of stored data, preventing unauthorized modifications and ensuring the integrity of the information. This way, the challenges that plagued previous research efforts can be addressed, and a more secure foundation for IoT data storage can be established, minimizing the potential for malicious attacks and unauthorized data tampering.

Previous research has overlooked the integration of deep learning and blockchain technologies working together for secure data storage. This novel research emphasizes combining these technologies cohesively, unlike earlier studies that focused separately on either deep learning or blockchain. By exploring their collaborative potential, this approach aims to revolutionize their capabilities and open new avenues for applications that were previously unexplored.

contribution introducing a novel This research introduces several significant contributions:

1) A groundbreaking framework is presented for post-accident investigation utilizing blockchain technology. This framework aims to revolutionize the process of examining vehicle accidents through a tamper-resistant and decentralized technology.
2) The study not only conceptualizes but also implements intelligent contracts within the blockchain system. These contracts streamline the seamless transfer of evidence through the blockchain, improving the transparency and integrity of data exchange.
3) A core emphasis of the research lies in the development of intelligent contracts that establish dynamic access controls for evidence and inquiry records. These controls are context-sensitive, factoring in variables such as the timing and condition of driver drowsiness. The results of these processes are then shared among stakeholders including truck drivers, logistics companies, law enforcement, and insurance providers.
4) Furthermore, in this study, we successfully integrated deep learning and blockchain technologies to operate collaboratively in a synchronized manner.
5) The project includes a crucial evaluation aspect wherein the performance of intelligent contracts and their functions is meticulously assessed. This evaluation included execution costs providing insights into the efficiency and effectiveness of the proposed system.

II. Literature Review

In this section, a review of literature is presented. The authors in [5] presented the use of NIR camera to assist in identifying drowsiness in drivers.The Yolov3 architecture outperformed the Viola Jones and dlib methods in detecting faces. For classification, a customized LeNet model was employed. The system achieved an impressive accuracy rate of 97% while operating at a speed of 20 frames per second. Instances where the face was obstructed, such as by a hand, were also considered.

Also, authors in [6] utilized Convolutional Neural Network (CNN) for real-time detection of driver fatigue, utilizing the CenterFace algorithm for facial recognition and the Haar-Classifier for eye feature extraction. The proposed model achieves high accuracy in identifying drowsiness, even in scenarios involving glasses or masks. Training accuracy is 97%, validation accuracy is 98 percent, and test accuracy for different eye conditions ranges from 97% percent to 92% percent. The CNN architecture comprises three consecutive 2D layers with batch normalization and 2D average pooling. It employed 32, 32, and 64 filters in the convolutional layers, with two dense layers using ReLU activation. The final layer uses sigmoid activation to determine eye state. Training involved rmsprop optimizer and binary crossentropy loss over 15 epochs. Notably, the method performs exceptionally well in real-time scenarios.

Furthermore, authors in paper [7] proposed a real-time drowsiness detection system that operates independently without wearables. It utilizes Faster R-CNN for eye region detection and CNN for eye state classification. The system, implemented on an Atmel microcontroller, serves as a prototype for monitoring driver fatigue and generating alarms in real time. This has applications in enhancing vehicular safety and accident prevention. The collected long-term data achieved accuracy of 97.6%, and the developed prototype could potentially integrate into intelligent transportation systems as a native solution.

Similarly, The authors in paper [8] proposed a YOLO-based detection model to identify abnormal behavior, specifically drowsiness, achieving over 95% accuracy in real-time. The system is effective for object detection and can be integrated with alarm systems.

Also, a study in paper [9] developed a driver drowsiness detection system using Raspberry Pi, utilizing a CNN to classify blinking and yawning as signs of drowsiness. The research employed a CNN with 4 convolutional and 27 hidden layers, utilizing ReLU activation in convolution and Softmax in the final layer. The CNN had an input image size of 244 x 244 and used an average pooling method. Training employed the Adam optimizer.Training on 1310 images, the CNN achieved over 80% accuracy in predicting driver drowsiness. The study also recommended placing the camera at a distance of at least

0.5 meters from the driver for improved classification accuracy [10].

III. Proposed System Model

The proposed system model is shown in Fig. 1. The model is subdivided into A, B, C, D. A represents a company truck for logistic purpose. B is mounted in front of steering wheel of the truck. B which is basically a Raspberry Pi running a trained deep learning algorithm for image classification is connected to a camera for monitoring the truck driver face to detect drowsiness state. Once a drowsy state is detected by the system, an alarm is triggered by the buzzer and the drowsy state information is forwarded into Ethereum blockchain network. C and D which represent police and insurance are connected to web 3.0 Ethereun blockchain network for auditability of the driver performance record.

IV. Methodology

The methodology used in this research is utilizing already existing deep learning algorithms such as VGG-16, CNN, MobileNet to learn images of driver drowsinees public dataset. The classification is binary using sigmoid activation function to classify the driver drowsiness condition (drowsy and non-drowsy). Once the result of the classication is drowsy, an alarm is triggered and the result is stored in a blockchain network using smart contract. Fig. 2 depicts the flowchart of the proposed system. The input images are used to train any of the three deep learning classifiers namely VGG-16, CNN and MobileNet for binary classification with the aim of comparison. Once the result of the drowsiness situation is drowsy, an alarm is automatically triggered to warn the truck driver of an impending accident. The drowsy state result is finally stored a Ethereum blockchain network via a smart contract whereby the logistic company, insurance company and police are participants of the Ethereum blockchain network and can have access to the driver performance record for auditability.

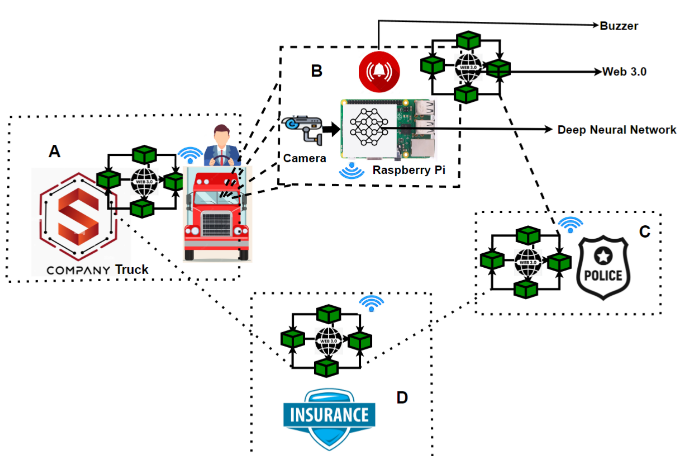

Fig. 1. Proposed System Model

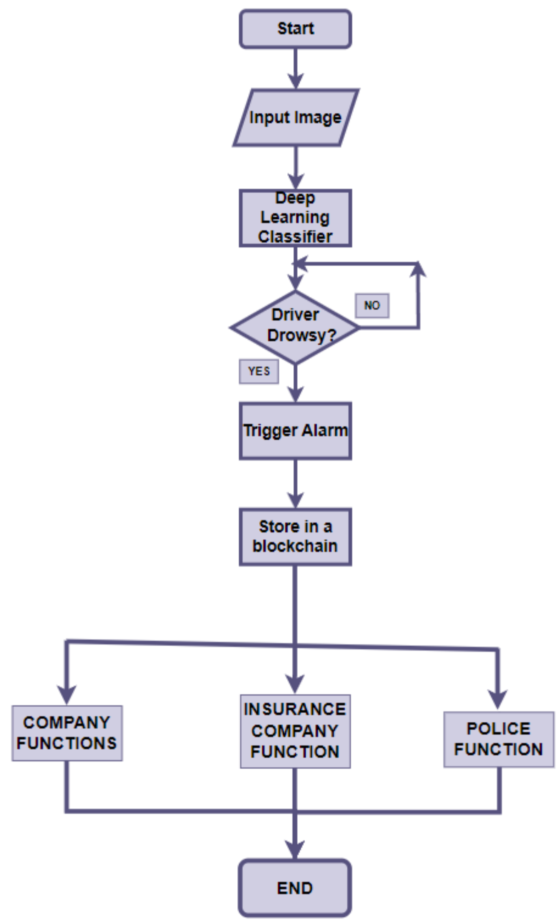

Fig. 2. The Flowchart of the proposed system

A. Implementation

The three deep learning classifiers were run on a Jupyter Notebook. Input grayscale image comprises of 3200 images for training and 400 images for validation. 100 epochs and 3 steps per epoch were used to train a MobileNet classifier. The input image was automatically resized to 224 by 224 using Tensorflow library in order to match well with MobileNet classifier. Also, 100 epochs and 3 steps per epoch with the same dataset were also used to train the VGG-16 classifier. The smart contract was written with Solidity programming language on a Remix integrated development environment. The smart contract was deployed on Ethereum test network and connected to the deep learning classifier using Infura and Web3.py python library for solidity smart contract.

V. Result

The performances of the three deep learning algorithms were checked using confusion matrix and accuracy. The confusion matrix for VGG16 and MobileNet classifiers are shown in Fig. 3. Also, the training/validation accuracy and loss graphs of VGG16 are shown in Fig. 4. Similarly, the training/validation

TABLE I
PERFORMANCE COMPARISON OF THE 3 DEEP LEARNING MODELS TRAINED

Methods	Training Time (minutes)	Testing Time (minutes)	Accuracy (%)
VGG16	90	41	50
CNN	100	45	50
MobileNet	75	28	50

and loss graphs of MobileNet are depicted by Fig. 5. The performance summary of the three deep learning models employed in this research is shown in Table I. From Table I, it can be deduced that VGG16 and MobileNet performed slightly better than CNN in terms of training time and testing time however, the three models have the same accuracy (50 percent).

Fig. 6 and Fig. 7 depict the smart contract interphace in Remix integrated development environment. The smart contract contains basically 5 functions namely recordDrowsyDriver(), getDrowsyDriverEventsCountForCompany(), getDrowsyDriverEventsCountForInsurance(), getDrowsyDriverEventsCountForPolice(), getDrowsyDriverEvents().The recordDrowsyDriver function is automatically called by Web3.py library once a deep learning classifier detects drowsiness state and stores the state in the blockchain network. The getDrowsyDriverEventsCountForCompany(), getDrowsyDriverEventsCountForInsurance(), getDrowsyDriverEventsCountForPolice() are used to keep track of the number of times drowsiness state was detected by the deep learning classifier for instance, 2 counts was detected as was shown in Fig. 10.

The getDrowsyDriverEvents function is used to record the blockchain address of the driver behind the steering wheel and also the timestamp during which the drowsiness state occured. The address of the driver and timestamp dusing which an event like dusring which an event occured gives stakeholders like company, law enforcement agents, insurance companies decentralized, trustworthy and evidence-based information source for post-accident root cause analysis or insurance premium estimation. Lastly, Fig. 8 depicts a histogram representing the execution cost of all the functions in the smart contract.

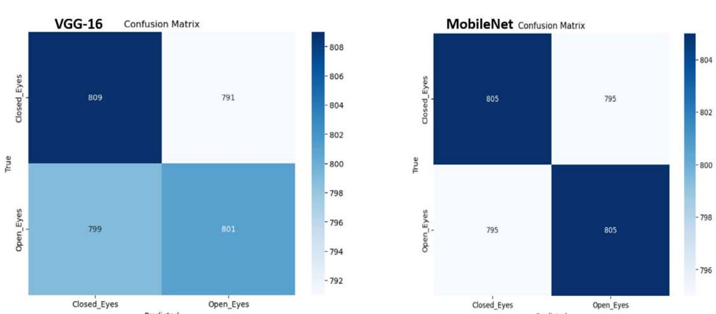

Fig. 3. VGG16 and MobileNet Confusion matrix

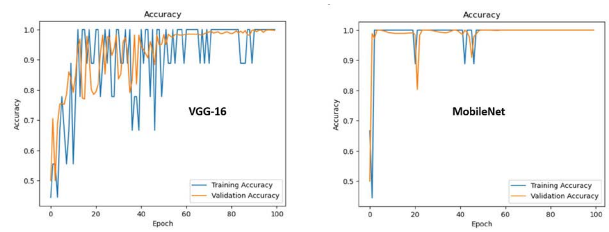

Fig. 4. VGG16 and MobileNet training and validation accuracy graph

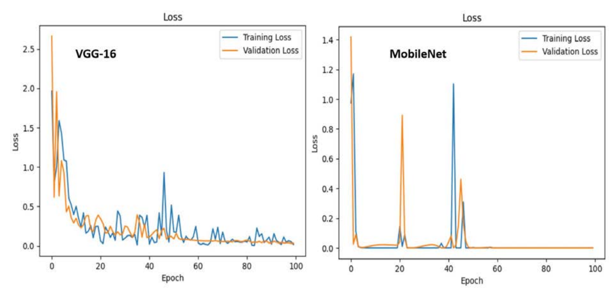

Fig. 5. VGG16 and MobileNet training and validation loss graph

Fig. 6. smart contract interphace for the driver drowsiness

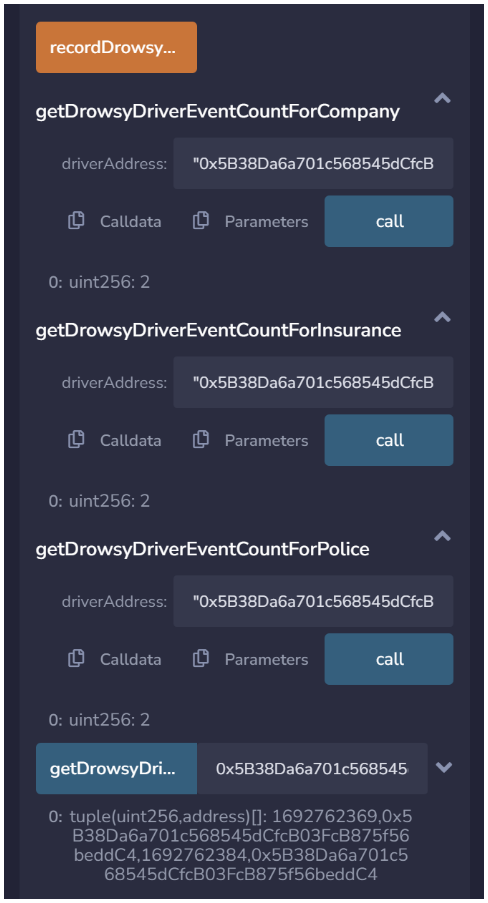

Fig. 7. smart contract for the driver drowsiness after calling recordDrowsiness function twice

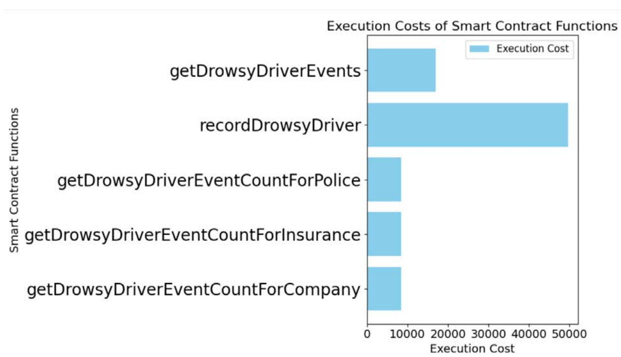

Fig. 8. smart contract fuctions execution costs

VI. Conclusion

In this research work, we have experimented with 3 deep learning algorithms to classify driver drowsiness and successfuly store the drowsy state result in a blockchain Ethereum network using a smart contract. The idea of classifying and detecting drowsiness state of a truck driver and storing the result in a blockchain was experimented and results have been documented showing that the 3 deep learning classifiers namely VGG16, CNN and MobileNet gave accuracy of 50% each on a public dataset, however, in terms of training time and testing time, VGG16 and MobileNet performed better than CNN as shown in Table 1. The result of the drowsiness state is stored in a blockchain network, hence, our main goal of combining deep neural network (VGG-16) with blockchain technology to run side by side was achieved. In future, we intend to improve the performance of the deep learning classifers through data augmentation, feature engineering, hyperparameter tuning and also include more driver driving events such as operating mobile phone while driving, talking to passengers, operating radio while driving etc while having Blockchain incorporated too.

Acknowledgments

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References

[1] I.-R. Adochiei, O.-I. Știrbu, N. I. Adochiei, M. Pericle-Gabriel, C.-M. Larco, S.-M. Mustata, and D. Costin, "Drivers' drowsiness detection and warning systems for critical infrastructures," in *2020 International Conference on e-Health and Bioengineering (EHB)*, 2020, pp. 1–4.

[2] P. Nandhini, S. Kuppuswami, S. Malliga, P. Srinath, and P. Veeramanikandan, "Driver drowsiness detection using deep learning," in *2022 6th International Conference on Computing Methodologies and Communication (ICCMC)*, 2022, pp. 1031–1036.

[3] V. Kalisetti, V. S. C. Vasarla, S. B. Kolli, R. Varaparla, V. Enireddy, and M. Mohammed, "Analysis of driver drowsiness detection methods," in *2023 Second International Conference on Electronics and Renewable Systems (ICEARS)*, 2023, pp. 1481–1485.

[4] C. Jacobé de Naurois, C. Bourdin, A. Stratulat, E. Diaz, and J.-L. Vercher, "Detection and prediction of driver drowsiness using artificial neural network models," *Accident Analysis & Prevention*, vol. 126, pp. 95–104, 2019, 10th International Conference on Managing Fatigue: Managing Fatigue to Improve Safety, Wellness, and Effectiveness". [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0001457517304347

[5] A. Sinha, R. P. Aneesh, and S. K. Gopal, "Drowsiness detection system using deep learning," in *2021 Seventh International conference on Bio Signals, Images, and Instrumentation (ICBSII)*, 2021, pp. 1–6.

[6] A.-U.-I. Rafid, A. I. Chowdhury, A. R. Niloy, and N. Sharmin, "A deep learning based approach for real-time driver drowsiness detection," in *2021 5th International Conference on Electrical Engineering and Information Communication Technology (ICEEICT)*, 2021, pp. 1–5.

[7] B. Ganguly, D. Dey, and S. Munshi, "An integrated system for drivers' drowsiness detection using deep learning frameworks," in *2022 IEEE VLSI Device Circuit and System (VLSI DCS)*, 2022, pp. 55–59.

[8] M. T. Soe, A. Zaw Min, H. T. Kyaw, M. Min Paing, S. M. Htet, and B. Aye, "Abnormal behavior detection in real-time for advanced driver assistance system (adas) using yolo," in *2022 IEEE Symposium on Industrial Electronics & Applications (ISIEA)*, 2022, pp. 1–6.

[9] S. S. I, R. Ramli, M. A. Azri, M. Aliff, and Z. Mohammad, "Raspberry pi based driver drowsiness detection system using convolutional neural network (cnn)," in *2022 IEEE 18th International Colloquium on Signal Processing & Applications (CSPA)*, 2022, pp. 30–34.

[10] V. Mansur and K. Shambavi, "Highway drivers drowsiness detection system model with r-pi and cnn technique," in *2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, 2021, pp. 1–6.