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Video-Based Abnormal Driving Behavior Detection Via Deep learning fusions

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***Abstract* – Video-based abnormal driving behaviour detection is increasingly vital for enhancing the safety of drivers and passengers, as well as for advancing autonomous driving technologies. Recent developments in deep learning techniques have significantly improved the detection of unusual driving behaviours by utilising the generalisation capabilities of sophisticated models and large datasets of video clips. This paper introduces three novel deep learning-based fusion models inspired by the densely connected convolutional network (DenseNet), marking a significant advancement in the field. These models aim to enhance the effectiveness of video-based abnormal driving behaviour detection, contributing to safer driving environments and the future of automated driving.**

***Keywords* – Video-Based Detection, Abnormal Driving Behaviour, Deep Learning, Densenet.**

I. INTRODUCTION

Abnormal driving behaviour detection is increasingly recognised as essential for enhancing road safety and advancing autonomous driving technologies, given that a significant percentage of traffic accidents are linked to driver misconduct. Recent advancements in deep learning models have improved the ability to detect these behaviours in real time, allowing for timely interventions to prevent accidents. The integration of high-resolution cameras and intelligent transportation systems in vehicles further enhances the continuous monitoring of driver behaviour. As the development of fully autonomous driving systems progresses, accurate and efficient detection of abnormal driving behaviour becomes crucial for ensuring safety and reducing traffic-related incidents. This study focuses on innovative methods that utilise high-resolution video data to monitor and analyse driver behaviour, contributing to safer driving environments and the advancement of autonomous vehicle technologies.

II. LITERATURE SURVEY

2.1 Importance of Abnormal Driving Behaviour Detection

Abnormal driving behaviour detection is essential for ensuring the safety of both drivers and passengers on the road. With the increasing prevalence of automated driving technologies, identifying risky driving patterns has become a priority. These detection systems aim to provide real-time notifications for abnormal behaviours, thereby significantly reducing the risk of accidents. Research in this field has highlighted the need for effective monitoring systems that can assess driver behaviour dynamically and offer timely interventions when necessary.

2.2 Methodologies and Tools Used

Various methodologies have been employed to detect abnormal driving behaviours, including the Driving Behaviour Survey, which focuses on anxious driving characteristics that are often overlooked. This survey helps in constructing measures that capture the nuances of driving under stress, identifying problematic behaviours that can lead to accidents. Additionally, advanced techniques such as artificial intelligence and machine learning play a crucial role in enhancing detection accuracy.

Systems utilising long short-term memory networks and regression residuals have emerged as effective tools for real-time behaviour analysis, providing valuable insights into driver performance.

2.3 Future Directions and Innovations

As the field of abnormal driving behaviour detection evolves, the integration of innovative technologies and comprehensive behavioural assessments will be paramount. Researchers are focusing on developing more sophisticated models that account for various internal and external factors influencing driving behaviour. These advancements not only aim to improve the effectiveness of driver assistance systems but also contribute to the broader goal of enhancing road safety and facilitating the transition to autonomous driving. Continued research and development in this area will be critical for addressing the challenges posed by abnormal driving behaviours and ultimately reducing traffic accidents.

III. EXISTING SYSTEM

Abnormal driving detection is increasingly leveraging deep learning techniques, with three primary schemes identified in the literature. The first scheme focuses on monitoring human physiological signals, such as electrooculogram and electroencephalogram data, using various sensors to detect signs of fatigue or distraction. The second scheme analyses facial details, including eye and mouth movements, to assess driver attentiveness. The rise of deep learning, supported by powerful computational hardware and large datasets, has led to the categorisation of models into deep generative learning models, like Variational Autoencoders (VAEs), and deep discriminant learning models. These advancements enhance the accuracy of detecting risky driving behaviours, contributing to the development of intelligent transportation systems aimed at improving road safety and reducing traffic accidents.

IV. PROPOSED SYSTEM

The study proposes deep learning-based fusion models for the automatic detection of abnormal driving behaviour, utilising the Kaggle State Farm distracted driver detection database. The results indicate a consistent trend of increasing accuracy concerning training epochs across all deep learning models, demonstrating effective training and convergence. As the training progresses, the accuracies stabilise, which is a positive indicator of the models' performance. Notably, three deep learning-based fusion models, including DenseNet and ResNet, outperform traditional CNN-based models such as CNN, Wide CNN, and Group CNN, showcasing their superior capabilities in detecting distracted driving behaviours.

Interestingly, the new deep learning-based fusion models reach a stable accuracy stage more quickly than DenseNet, requiring fewer training epochs to achieve similar performance levels. This rapid convergence suggests that these models not only enhance detection accuracy but also exhibit significant robustness in their performance. The findings underscore the potential of advanced deep learning techniques in improving the reliability and efficiency of abnormal driving behaviour detection systems, ultimately contributing to enhanced road safety measures.

V. MODULE DESCRIPTION

1) **Generate & Load AWGRD Model:**

Using this module AWGRD train model will be generated from input images downloaded from the Kaggle State Farm Distracted Driver Detection Database. This database contains 22424 images, and the model is built using all those images.

2) **Upload Video:**

Using this module, we can upload the video to this application and then start playing the video using the Python OPENCV library.

3) **Start Behaviour Monitoring:**

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Using this module, we will extract each frame from video and then resize image according to AWGRD Model. AWGRD Model will be applied to this frame to predict the behaviour of the driving person. All behaviours will be displayed while playing the video.

VI. Algorithms Based on CNN Deep Learning Models

6.1 Wide Group Densely (WGD) Network: Technically, WGD takes important issues of deep learning models, i.e., the depth, the width and the cardinality, into consideration when designing its model structure based on Dense Net. This model uses deep features from the input training model to get better prediction accuracy.

6.2 **Wide Group Residual Densely (WGRD) Network:** The most significant change of WGRD with respect to WGD is that the idea of residual networks is incorporated in WGRD. In this algorithm input image will pass from one layer to another residual layer to have the best features from the trained input image to get the best accuracy.

6.3 Alternative Wide Group Residual Densely (AWGRD) Network: This algorithm works similarly to the above two algorithms, but while passing input data from one layer to another, this algorithm will take superpositions of previous layers, which have the best features from all layers and will have better prediction accuracy. Due to super positions extraction training efficiency will undoubtedly become higher.

VII. Results Explanation

In below screen, click on 'Generate & Load AWGRD Model' button to generate AWGRD train model. All model information we can see in black console after clicking on button.

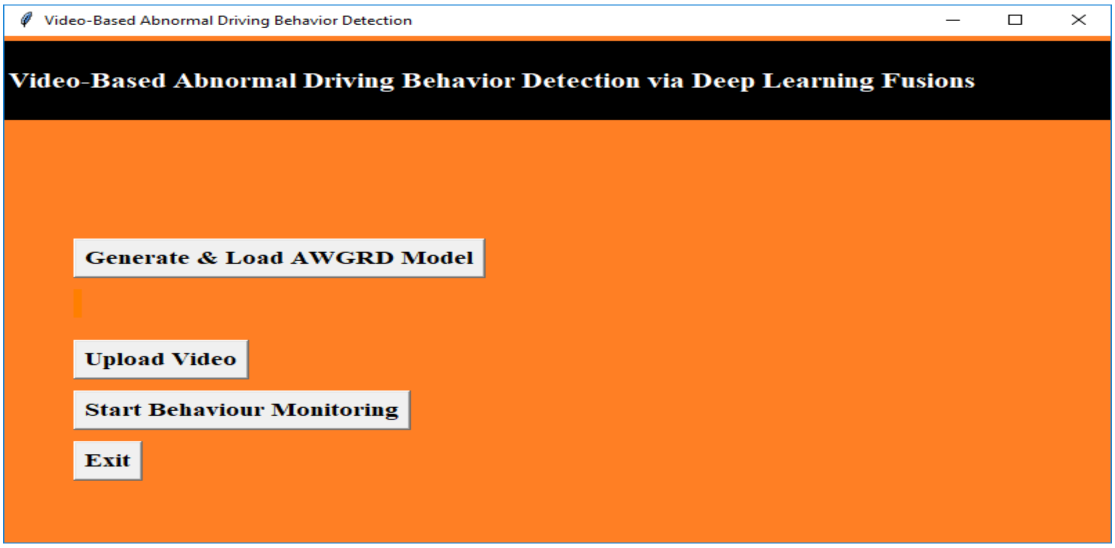

Figure :1 Generate & Load AWGRD Model

In the screen below, we can see that the model is generated, and in the screen below, we can see all details.

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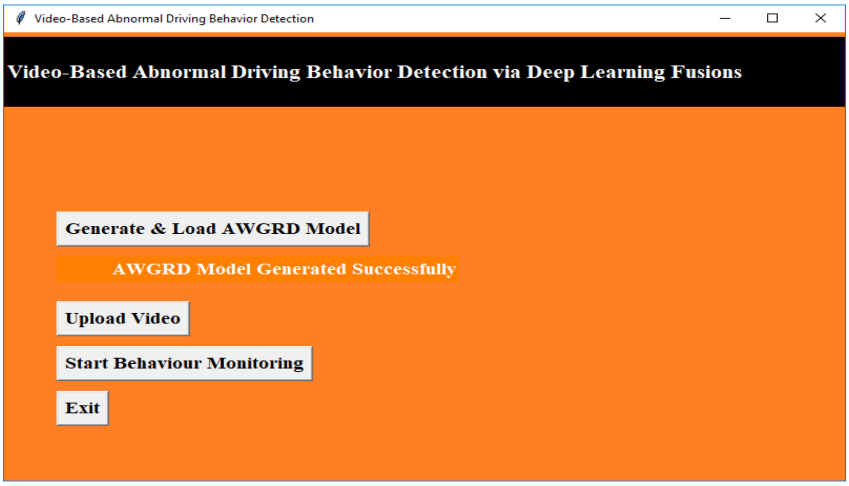

Figure 2 Video-Based Abnormal Diving Behaviour Detection via Deep Learning Fusion

In the below screen dense model using AWGRD is created. Now click on 'Upload Video' button to upload video.

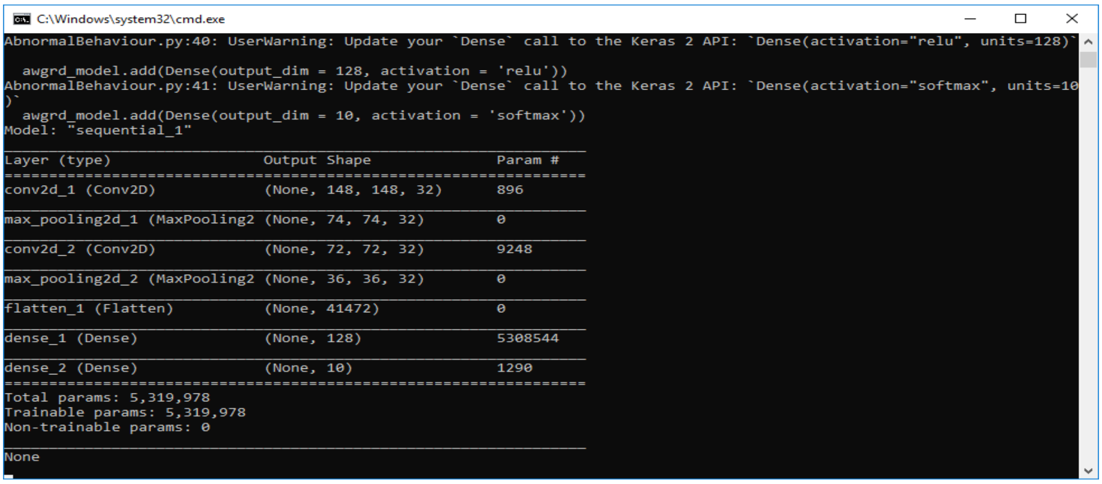

Figure 3. In the below screen application detected user is using/talking on the phone.

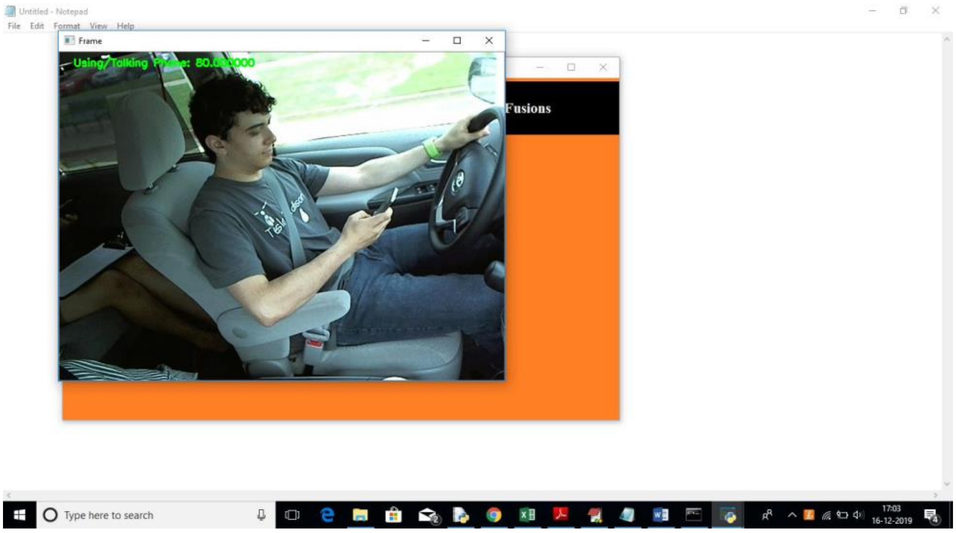

Figure 4. In the screen below, we can see the user is trying to start the Radio. Similarly, other detections will also be performed

Figure 5: Abnormal driving behaviour detection

VIII. Conclusion

The video-based abnormal driving behaviour detection study is highly important nowadays, as it is a reliable and automatic method to ensure the safety of drivers. Also, it receives vast popularity as it is an essential step to realise fully automatic driving (i.e., particularly in Level-3 and Level-4 stages according to the ''autonomous driving'' definition provided by the US Department of Transportation's National Highway Traffic Safety Administration). In this study, three novel deep learning-based fusion models are introduced to fulfil the video-based abnormal driving behaviour detection task. Technically, these new models are inspired by the popular DenseNet, which was proposed in recent years. For WGD, it emphasises important issues of the design of modern deep learning models, including the depth, the width, and the cardinality. The width and the cardinality of WGD significantly increase, therein. For WGRD and AWGRD, they are more sophisticated as the important idea of residual networks with superpositions of previous layers is incorporated.

IX. Future Scope

Algorithms based on CNN deep learning models.

1) **Wide Group Densely (WGD) Network:** Technically, WGD takes important issues of deep learning models, i.e., the depth, the width and the cardinality, into consideration when designing its model structure based on Dense Net. This model uses deep features from input train model to get better prediction accuracy.
2) **Wide Group Residual Densely (WGRD) Network:** The most significant change of WGRD with respect to WGD is that, the idea of residual networks is incorporated in WGRD. In this algorithm input image will pass from one layer to other residual layer to have best features from train input image to get best accuracy.
3) **Alternative Wide Group Residual Densely (AWGRD) Network:** This algorithm works similar to above two algorithms but while passing input data from one layer to other, this algorithm will take super positions of previous layers which has best features from all layer and will have better prediction accuracy. Due to super positions extraction training efficiency will undoubtedly become higher.

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