ECG-Based Driver's Pressure Location Utilizing Profound Exchange Learning And Fluffy Rationale Approaches

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Abstract: The stress experienced by drivers is modelled in this article utilising multiple pre-trained networks. Seven pre-trained networks were utilised to extract features from ECG-based scalogram images in order to automatically increase the detection performance: Google Net, DarkNet-53, ResNet-101, InceptionResNetV2, Xception, DenseNet-201, and InceptionV3. To lessen the likelihood of car accidents and health problems caused by drivers' stress, driver stress detection has emerged as a major area of study. The majority of the prior research in this field relies on feature extraction techniques to manually classify the driver's stress levels using typical machine learning models. Finding the best characteristics using these methods is never easy. More recently, deep learning methods have been developed to automatically build trustworthy features and classify data with great accuracy. However, issues with gradient disappearing or growing are encountered by large deep learning models. Building a large dataset from beginning might also be a challenge when training a full network. In order to circumvent these issues and save computational time and money, this study is constructed on top of the deep transfer learning technique. Using electrocardiogram (ECG) readings, seven different approaches are suggested for determining the stress levels of drivers in real-world scenarios. In order to categorise the driver's stress level, three separate CNNs are trained in advance. We looked at the ECG signal data from seven different algorithms—InceptionV3, Xception, Resnet101, Google Net, InceptionResnetV2, Densenet201, and Darknet53—to see how well the pre-trained algorithms predicted stress from DRIVERS. Xception provides algorithms with a high level of accuracy. Several machine learning algorithms have been created to attempt to alert drivers who are stressed, as they are a known accident-causing factor. One potential issue with these algorithms' prediction accuracy is that they are trained using features that are developed manually instead of utilising exact calculations.

Keywords: Darknet53, Xception, Google Net, Convolutional Neural Network (CNN), and Electrocardiogram (ECG).

1.Introduction

One of the world's most undesirable positions is driving [1], [2]. Viable driving exercises generally require full use of both physical and mental abilities because of

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the mind boggling and risky nature of driving [3]. While driving in an unsafe circumstance, the thoughtful sensory system turns out to be more dynamic, making the driver's psyche go into intense pressure. This can keep the body from answering fittingly on time and result in serious misfortunes [4-6]. Contrasted with laborers in different areas, proficient drivers are bound to encounter pressure [7, 8]. Stress adversely affects driving way of behaving, which every now and again brings about car crashes that truly hurt the two individuals and vehicles every year [9], [10]. Drawn out pressure may likewise expand the gamble of mental, stomach related, and cardiovascular problems [11], [12].

Various things, like individual conditions, ecological variables, and human blunder, can prompt risky circumstances [13]. Blunders committed by drivers represent around 90% of car crashes. The most well-known human blunders (41%) are brought about by interruption, distractedness, mental strain, and unfortunate perception. In [14].

Data from the body, climate, and physiology can be utilized to decide a driver's feelings of anxiety [15]. The physiological signs that are most ordinarily utilized in the investigation of driver feeling of anxiety location are breath (RESP), galvanic skin reaction (GSR), and electrocardiogram (ECG). It is feasible to consolidate different physiological signs to all the more precisely decide the driver's feeling of anxiety [6].

2.Literature Survey

It does discuss prior research and methodologies related to driver stress detection, which can be considered as part of the literature survey. Here's a breakdown of the relevant points:

Prior Research Overview: The text acknowledges previous studies in driver stress detection, highlighting the reliance on conventional machine learning models with manual feature extraction techniques. It suggests that these approaches may not be optimal due to the difficulty in extracting the best features.
Transition to Deep Learning: The text discusses the transition to deep learning techniques for automatic feature extraction and classification, citing their potential to improve accuracy. However, it also mentions challenges such as gradient vanishing and the need for large datasets.
Deep Transfer Learning Approach: The paper proposes a deep transfer learning approach to address these challenges. By leveraging pre-trained networks, it aims to enhance detection performance while saving computational time and cost Pre-Trained CNNs: Seven pre-trained Convolutional Neural Networks (CNNs) are mentioned, including InceptionV3, Xception, Resnet101, Google Net, InceptionResnetV2, Densenet201, and Darknet53. The selection of these networks indicates a comprehensive exploration of different architectures for stress detection.
Evaluation of Models: The text highlights the evaluation of ECG signal data using

the selected pre-trained algorithms to assess their effectiveness in predicting stress levels in drivers. Xception is specifically noted for providing high accuracy across all algorithms.

Need for Accurate Predictions: The text emphasizes the importance of accurate stress detection in drivers to prevent accidents and health complications. It suggests that existing machine learning algorithms may suffer from prediction inaccuracies due to reliance on manually crafted features.

3. Proposed method

A particular kind of convolutional neural network (CNN) known as a ResNet is one that was first described in the 2015 paper "Deep Residual Learning for Image Recognition" by HeKaiming, Zhang Xiangyu, RenShaoqing, and Sun Jian. Computer vision applications are often driven by CNNs.

A convolution neural net architecture called VGG16 is employed in image recognition. Using 16 layers with weights, it is considered one of the best vision model designs to date.

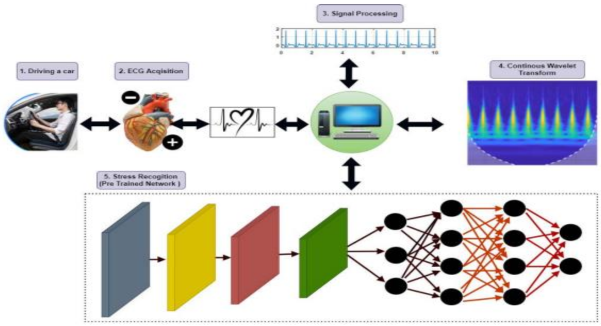

Fig.1. Architecture Diagram

4. RESULT AND DISCUSSION

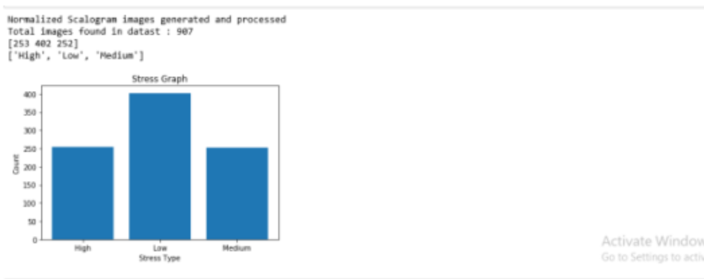

Fig. 2. Stress Graph based on Images

Fig. 3. Scalogram images from signals

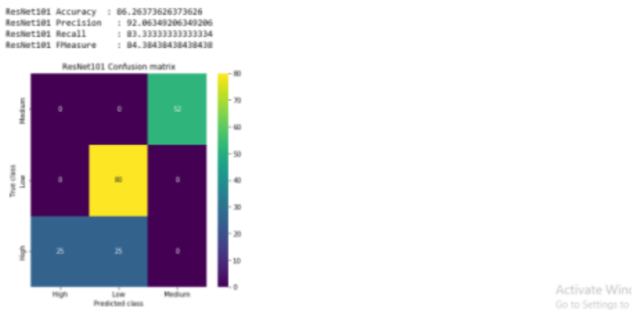

Fig. 4. ResNet 101 Confusion Matrix

Fig.4. In the figure above, we can see that Resnet101 achieved an accuracy of 86%. In the confusion matrix graph, the x-axis shows the predicted labels and the y-axis shows the true labels. The count gauge, running from left to right, shows the number of correct predictions, while the remaining count represents the number of incorrect predictions. We are currently training the Xception algorithm, and the output is below.

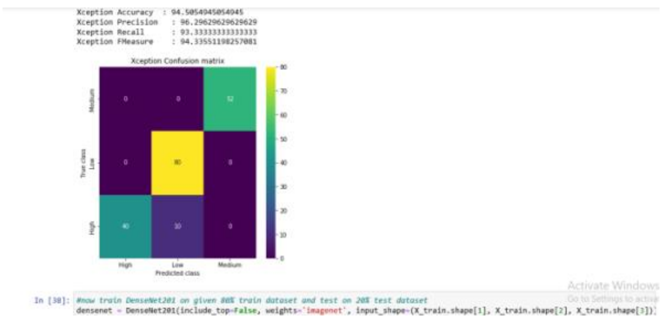

Fig. 5. Xception Confusion Matrix

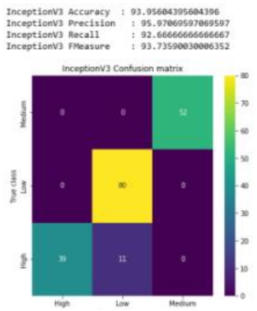

Fig. 6. InceptionV3 Confusion Matrix

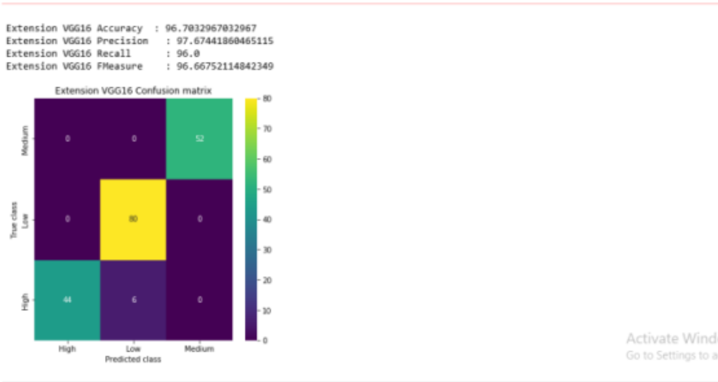

Fig. 7. with Extension VGG16 Confusion Matrix

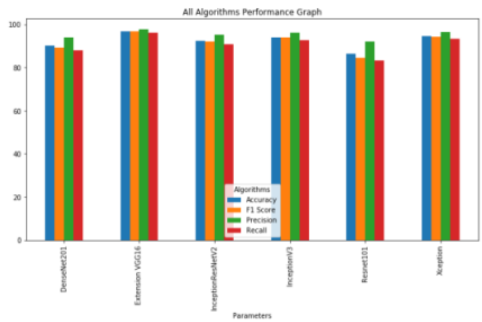

Fig. 8. Performance Graph of All Algorithms

	Algorithm Name	Precison	Recall	FScore	Accuracy
0	Resnet101	92.063492	83.333333	84.384384	86.263736
1	Xception	96.296296	93.333333	94.335512	94.505495
2	DenseNet201	93.877551	88.000000	89.312140	90.109890
3	InceptionResNetV2	95.035461	90.666667	91.891651	92.307692
4	InceptionV3	95.970696	92.666667	93.735900	93.956044
5	Extension VGG16	97.674419	96.000000	96.667521	96.703297

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Fig. 9. Algorithms Performance Metrics

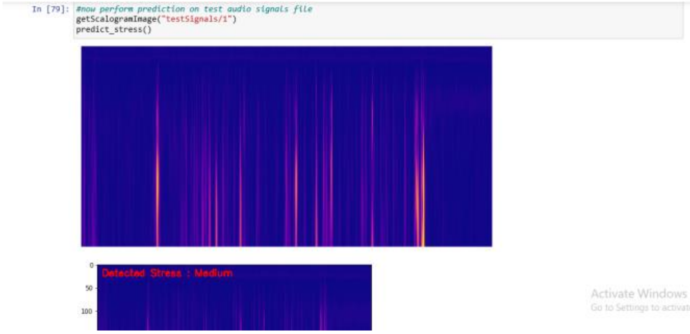

Fig. 10. High Stress Detection

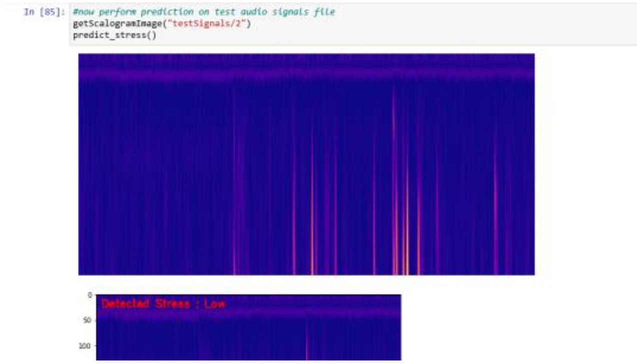

Fig. 11. Low Stress Detection

5. Conclusion

Several proposed models for real driver stress make use of various pre-prepared networks. By applying seven pre-trained networks—GoogLeNet, DarkNet-53, ResNet-101, InceptionResNetV2, Xception, DenseNet-201, and InceptionV3—to remove highlights from ECG-based scalogram photos, the localization performance was improved.

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