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Transfer Learning-based Driver Distraction Detection

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***Abstract*—Due to driver's preoccupation, there have been more accidents on the roads recently all around the world. One of the key explanations is attributed to human behavior. Accidents have been linked mostly to drivers' distraction. This sudden road crush frequently causes injuries, property loss, or even fatalities. The automated interpretation of the driver's behavior is one of the trickiest subjects in the field of intelligent transportation systems (ITSs). This study looks on the human action recognition aspect of distracted driving posture recognition. There have been several reports of inattentive driving causing auto accidents. The goal is to use cutting-edge transfer learning techniques like MobileNetV2 and DenseNet to identify distracted driving activities more effectively. As driving is a complex task, it requires complete attention of the driver. Distractions of the driver can be due to talking phone calls, texting, talking to another passenger, drinking, operating radio. To identify distractions while driving, it is crucial to observe and evaluate the driver's behavior. Images of the driver serve as the main source of data and that comprises of face, arms, and hands of the person inside the car. To decrease vehicle accidents and enhance transportation security, it is extremely desirable and has received a significant amount of study to develop a system that can detect distracted driving. In this study, transfer learning models like DenseNet and MobileNetV2 are used to classify and detect driver distraction. The best performance was produced by MobileNetV2, which has an accuracy of 93.8.**

***Keywords*—Deep Learning, Distractions, Inattentiveness, Transfer learning, Safe Driving**

I. INTRODUCTION

The World Health Organization (WHO) performed a study that found the thousands of individuals die in traffic accidents annually. Driver distraction has contributed to an increase in overall fatalities. Distraction is referred as "the driver's inattention towards driving". In other words, despite maintaining a safe driving posture, the person is distracted from the task of driving mentally. Drivers admit to use one or more of the following while operating a vehicle: taking phone calls, responding to messages, operating the radio, chatting with another passenger, eating or drinking while driving, checking maps, watching videos, and surfing the web.

One of the most critical reasons that causes to major car accidents in India is inattentive driving. The public should become more concerned about this issue to decrease the death rates due to driver distraction. Researchers have investigated the application of artificial intelligence to comprehend unsafe driving behaviours help to create driver aid and alert systems in an effort to lessen this issue. By using the ability to forecast distracted driving at an early stage, accidents can be prevented. Research suggests that early detection of distracted driving, backed by visuals, is a significant component in minimizing the severity of accidents. By detecting the distraction using a better model can quickly make a driver to refocus on the road and the controls, a distracted driver can take necessary actions in a timely manner. Thus, a crucial system component in these cars is distracted-driver detection. A system that can identify distracted driving is extremely desirable and has sparked a lot of research interest in order to decrease vehicle accidents and enhance transportation safety. Current systems employ sensors to identify distractions, but they also require time-consuming human input for detection, and strategies like two-step architecture can't achieve an ideal trade-off, leading to inaccurate categorization of distractions.

To develop an accurate and robust methodology for identifying distracted drivers, it is crucial to concentrate on recognizing manual distractions when a person isn't paying attention to safe driving and pinpointing the source of the distraction. To tackle this issue transfer learning-based approach is used. The development and utilisation of models that allow a system to learn the necessary information based on past experience or data sets is the focus of machine learning, particularly deep learning. Deep learning algorithms have demonstrated outstanding performance when obtaining various critical features from real-time computer vision and image processing due to the massive computing capabilities. The proposed system classifies the distractions more quickly than others, and it also uses less resources to build an experimental setup. To address the resource limitations, it can be parameterized to low-power models using these models.

In order to reduce fatalities, it is crucial to detect the distractions of a driver, which plays a key role to resolve this issue. By making use of transfer learning based methods like

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MobileNetV2 and DenseNet are made use in detecting distraction.

The study is organised as follows, Section II provides the literature study of driver distraction detection using deep learning and machine learning based techniques. Section III gives insight about methodology for detecting driver distraction followed by Section IV, results are displayed. Subsequently, in section V, it concludes the paper.

II. Literature Study

A distracted driver is at blame for roughly one in five car accidents. To create a reliable and precise approach to identify distracted drivers, they demonstrated a system that recognizes distracted driving using CNN. For this work, the VGG-16 architecture is altered, and various regularization methods are suggested to enhance performance [1]. To observe and assess the behavior of the driver while they are on the road to spot distractions and reduce the frequency of accidents they used transfer learning architectures like CNN, VGG-16, ResNet50, and MobileNetV2 [2]. Techniques like the driver distraction monitoring strategy that makes use of stacked BiLSTM Networks and CNNs are useful for extracting the spatio-spectral characteristics from the images [3]. The automated interpretation of the actions of the drivers is one of the most challenging applications of smart transportation systems. This study looks at the posture recognition of distracted drivers as a part of the framework for recognizing human behaviors. Numerous incidents of distracted driving leading to car accidents have been made. Their objective is to make it easier to detect distracted driving. The developed technology makes use of a dashboard camera that can detect distracted driving in 2D images [4]. Approach like fuzzy logic algorithm is used to evaluate distraction of a driver [5]. In order to handle large data machine learning algorithms are replaced with deep convolutional neural network to provide efficient outcomes of distraction [6]. WHO survey states that a driver's carelessness is to cause for one-fifth of accidents. The sort of distraction may be detected and predicted with the use of characteristics like pupil diameter, hands placement, and head placement [7]. The actual driver's focus of attention and the driver's focus of interest metrics can be used to determine driver distraction. They developed a complex 3D residual network with an encoder-decoder and an attention mechanism [8]. This research investigated semi-supervised approaches using Laplacian support vector machines and Laplacian support vector machines techniques in actual driving situations to decrease the significant expense for gathering labelled data in driver distractions [10]. The growing use of so called partially autonomous driving assistance systems and in-vehicle information systems (IVIS) has drawn attention to the need for increased safety measures [11]. Drive-Net is an automated supervised learning method that combines a random forest and a convolutional neural network (CNN) to automatically classify images of drivers [12]. Single Convolutional Neural Networks, such as MobileNet, Inception and ResNet, are effective for analyzing the distractions of a driver[13].

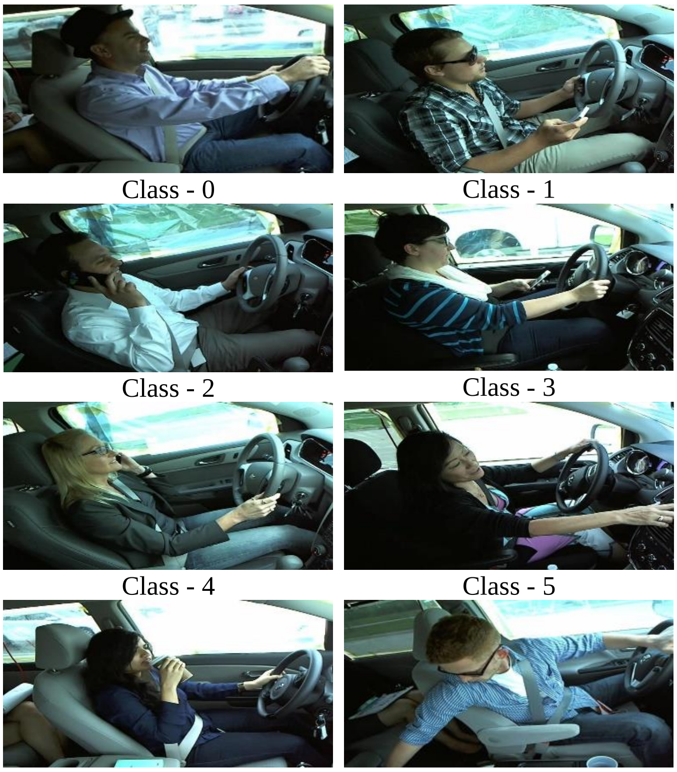
III. Methodology

A. Dataset Description

The dataset entitled State Farm's Distracted Driver Detection is utilized in the study to assess driver carelessness. 17939 of these images are used to train the model. The training dataset is divided into 10 classes, with each class comprising around 2200 images, each based on the characteristics of the distracted driver. Out of which 4485 images are taken for validation. The different classes include safe driving, reaching behind, using the radio, talking on the phone with the right hand, drinking, texting with the left hand, doing hair and makeup, talking on the phone with the left hand, texting with right hand and speaking to another passenger.

TABLE I. Distracted Behaviour Classes

Class	**Behavior**
Class 0	Safe Driving
Class 1	Texting on right hand
Class 2	Cell phone talking on right-hand
Class 3	Texting on left Hand
Class 4	Cell phone talking on left-hand
Class 5	Operating the radio
Class 6	Drinking
Class 7	Reaching Behind
Class 8	Hair and makeup
Class 9	Talking to passengers



Class - 6 Class - 7

Class - 8 Class - 9

Fig. 1. Images of distracted behavior classes.

Table I. shows the different classes and of the driver distractions. Fig. 1. Depicts the different images of distraction behavior.

B. Image Processing

Firstly, import the libraries that are required for the process of distraction detection. Then configure the training and validation data generators and direct them to the image directories. The adjustments that will be made to all the images by the training data generator to augment the dataset size. And provide the scaling factor for the validation data generator. The Models are defined in next steps. The training dataset uses a total of 80% of the data.

Different methods, including MobileNetv2 and DenseNet, were used to train the proposed model. MobileNetV2 has the highest accuracy of the two models that were employed above since it outperformed the other algorithm. By applying an optimizer called Adam Optimizer and an activation function named SoftMax Activation to implement the above algorithms. Scaling the images between 0 to 1 and resizing is done as a part of preprocessing step. This is the actual process that occurs in preprocessing phase.

C. SoftMax Activation

It is a function which is used in output layer of the neural network to classify a multiclass classification problem.

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}}$$

The formula for calculating an activation function is mentioned as above.

D. Adam Optimizer

It is an optimization technique which is used to update network weights based on its training data. It uses a combination of two gradient descents by taking weighted average into consideration.

E. MobileNetV2

It is a light weight model used for classification formulated by Google. It is the second version of MobileNet models. It performs effectively due to its minimal weight both in embedded systems and mobile systems. A sizeable image dataset has been utilized to train MobileNetV2. It allows the model to learn competently so that precise results can be anticipated. The new CNN layers are supported by the MobileNetV2 are linear bottleneck and the inverted residual layer.

Both the inverted residual and bottleneck block have three layers:

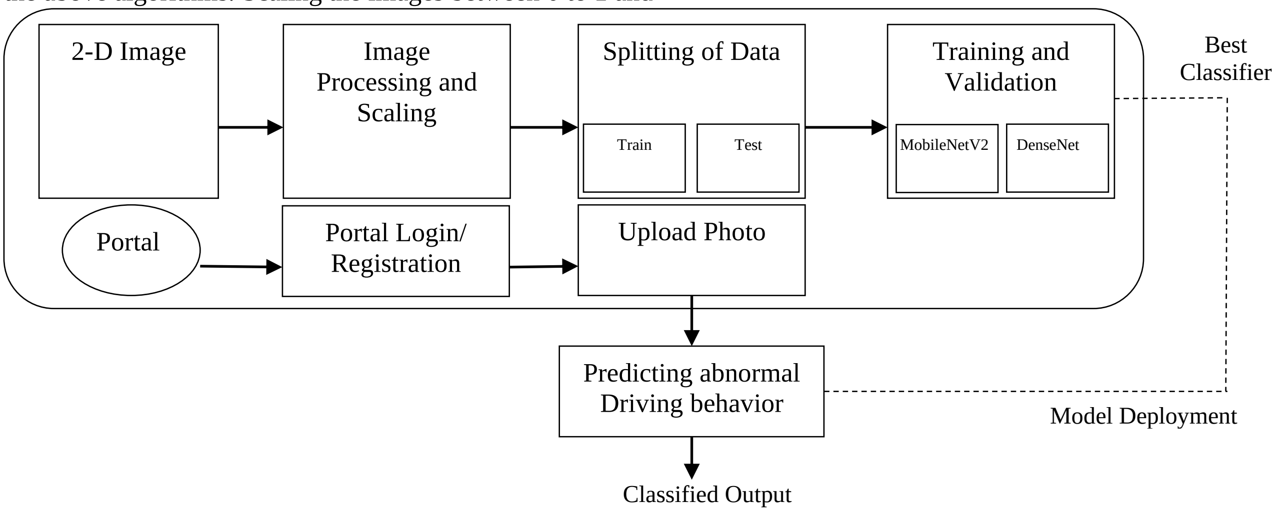


Fig. 2. Systematic representation of the proposed system.

- The 1x1 convolution with ReLU6 constitutes the first layer.
- A depth-wise Convolution using ReLU6 makes up the second layer.
- A nonlinear 1x1 convolution constitutes the third layer.

F. DenseNet

Leveraging dense blocks, a form of convolutional neural network called DenseNet uses dense connection between layers to integrate all the layers to each other directly that is the first layer is linked to its consecutive n number of layers and the second layer is linked to its successive layers. This is the main feature of this algorithm that one layer gets connected to its successive layers. Due to interlinking between the layers the flow of information is maximized. An extra piece of information is gotten by the successive layer from the previous layer. The feature maps are forwarded to the later layers so that it maintains its feed forward individuality. This layer's output is known as a transition layer, and it employs max-pooling to minimize the size of feature maps. It has higher memory efficiency and computational efficiency. It also increases its parameter efficiency. It results in improvement of gradient flow.

Each dense layer consists of two convolutions with kernels that are 1x1 and 3x3 in size. The existing channel has to be decreased by 50 % of its original size. There is a two stride average pooling layer with 1x1 convolutional layer and 2x2 layer. Using the algorithms like MobileNetv2 and DenseNet it is able to solve and predict multiclass classifications accurately.

A web application is created in which a user needs to sign up by giving their credentials like username, mobile number, email, password. After successful registration, user will be entering into login page where they provide details of their account like username, password. After validation of credentials, then the user can upload the images and know about the abnormal behaviour of the driver.

G. Web Application

After establishing the python environment and essential modules, the web application is ready for execution and results. It is a flask-based web application, and a new user must first register or sign up. The registration is done by giving credentials that include username, mobile number, email and password. A previously registered user can use their valid credentials to log in to the web application directly by entering the username and password. Only when

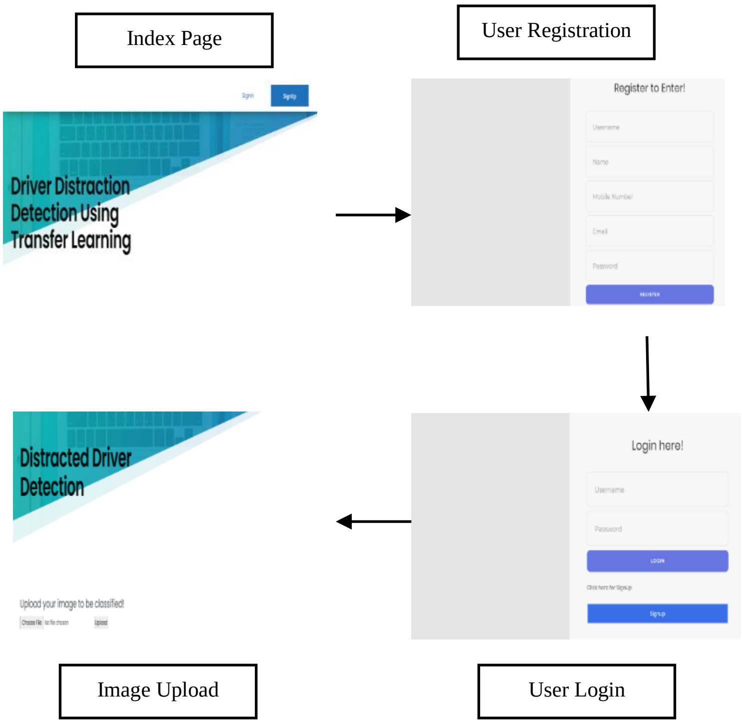


Fig. 3. Web application for classifying the abnormal behaviour of the driver.

they have successfully logged in, then they get granted access to know the different distractions. They can upload the image and can click on the upload button. Then the system goes through the process to give results. In this way the distraction of the driver is detected.

Fig. 2. Represents the web application used in the paper, where the user has to enter their details consisting of username, password, mobile number and their email address. Once this registration gets done the user's details are stored in the database automatically. Hence the user can just login the next time. Once the user logs in they have to just upload the concerned image which they want to use for prediction. Once the image gets uploaded the model predicts the type of distraction.

IV. RESULTS

The outcomes generated by the proposed system are examined in this section. Figures 3 and 4 respectively depict the MobileNetV2 model's loss and accuracy curves. Using the MobileNetV2 method, an accuracy of 93.8% is achieved.

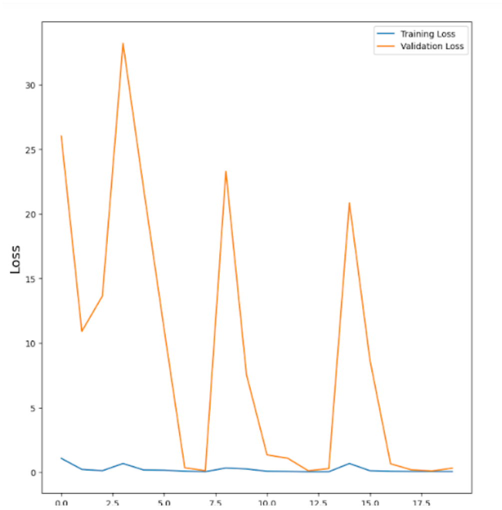


Fig. 4. Loss curve of MobileNetV2

The validation loss curve vs Training loss curve in Fig. 3, represents MobileNetV2's loss curve. In the above graph it is clearly noticeable that the validation curve is on the declining stage.

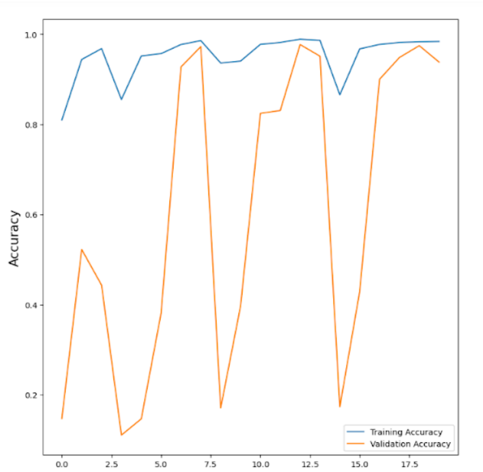


Fig. 5. Accuracy curve of MobileNetV2

The training accuracy vs validation accuracy curve in Fig. 4, represents MobileNetV2's accuracy curve. In the above graph it is clearly noticeable that the validation curve is on the increasing stage. Hence, it can prove that the training accuracy is greater than the validation accuracy.

The outcomes generated by the suggested system are examined in this section. Figures 5 and 6 respectively display the loss and accuracy curves of the DenseNet model. The DenseNet method gave us an accuracy of 84.08 %.

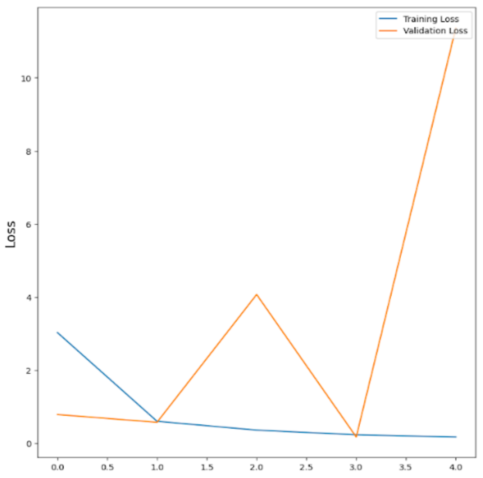


Fig. 6. Loss curve of DenseNet

The validation loss curve vs Training loss curve in Fig. 5, represents DenseNet's loss curve. In the above graph it is clearly noticeable that the training loss curve is high until a certain point, but it decreases right after that linearly. Hence, it can be proved that the training loss keeps on decreasing.

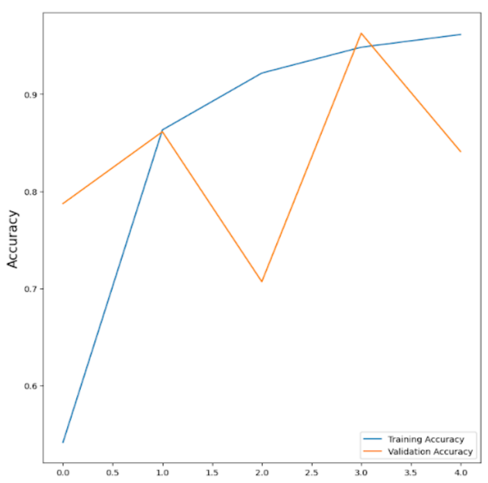


Fig. 7. Accuarcy curve of MobileNetV2

The training accuracy curve vs validation accuracy curve in Fig. 5, represents DenseNet's accuracy curve. In the above graph it is clearly noticeable that the training accuracy curve is low until a certain point and it increases right after that. Hence, it can be proved that the training accuracy keeps on increasing.

TABLE II. PERFORMANCE METRICS

Model	**Training Accuracy**	**Validation Accuracy**	**Training Loss**	**Validation Loss**
MobileNetV2	98.39	93.81	5.54	31.8
DenseNet	96.13	84.08	17.09	11.36

TABLE III. ARCHITECTURAL COMPARISON OF MOBILENETV2 AND DENSENET

SL	Properties	MobileNetV2	DenseNet
1	Image	224×224×3	224×224×3
2	Weight	Imagenet	Imagenet
3	Activation function	Softmax	Softmax
4	Total parameters	3.5 million	20 million

By comparing the outcomes of the above- mentioned algorithms from Table III and Table IV, MobileNetV2 has surpassed the DenseNet model in terms of accuracy. Given the high accuracy values of MobileNetV2, it provides insights that MobileNetV2 has outperformed DenseNet. Prediction of distraction is done by making use of algorithms like MobileNetV2 and DenseNet.

V. CONCLUSION AND FUTURE SCOPE

Around the world, distracted driving is a significant contributor to road accidents. This proposed system involves creating models which utilize MobileNetV2 and DenseNet to identify driving distracted behaviors. It is evident that MobileNetV2 displayed accuracy that was 93.8% higher than DenseNet's 84%.

The following can be applications of the proposed model, if it is deployed in a car, it can alarm or notify the driver if they are inattentive. Semi-autonomous cars have the ability to take control if the driver is not focused on the road. The government can utilize this to enact rules requiring safe and attentive driving. These formulas can be used by auto insurance firms when modifying auto plans.

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