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EXPLORING CONVOLUTIONAL NEURAL NETWORKS FOR AUTOMATED DRIVER DROWSINESS DETECTION

Raphael O. Oloke[1], Akinwumi F. Akinleye[2], Olaoluwa O. Ogunsakin[3]

[1,2,3] Department of Electrical and Electronic Engineering, The Federal Polytechnic, Ado-Ekiti, Ekiti-State

E-mail: [1]Princeoloke@yahoo.com; [2]akinleyeakin@yahoo.com; [3]oogunsakin1@yahoo.co.uk.

ABSTRACT

Over 93% of road accidents occur in developing nations, and each year, approximately 1.3 million people die as a result of these accidents. It is estimated that by the year 2030, road injuries will rank as the seventh-largest cause of death globally. Although several strategies have been employed to mitigate against this problem, however, most of these approaches are time-consuming and involve the driver wearing gadgets for monitoring which most times are very uncomfortable. In addition, complex machine learning approaches such as K-Nearest Neighbour (KNN), Random Forest Classifier (RF), Support Vector Machine (SVM), Transfer Learning AlexNet and Convolutional Neural Network (CNN) have made significant impact on solving this problem. This research work developed an ensemble model for identifying drowsiness in drivers using three CNN lightweight models—Inceptionv3, MnasNet, and MobileNetv2. These models were selected because of their compatibility and ease of use in embedded systems and smart devices. Stacking ensembles combine the best layers of the three CNN models to create a metaclassifier to improve the performance of the created model. A balanced, locally acquired dataset was collected for the purpose of this study. The dataset comprises a total of 4,000 images that are evenly distributed across the four categories for proper implementation of the model. Each image was 224 by 224 pixels. To improve performance, the 4,000 photos in total were further separated into four classes: yawn, no yawn, eye open, and eye closed. The brand-new dataset named DDDS was further split into ratios of 80:10:10 for the training, validation, and testing sets of the model. The ensemble model's testing accuracy is 91.25%, the average precision score is 91%, the average recall is 92.25%, and the average F1 score is 91.63%, which shows that it can identify fatigued drivers. The developed system was also compared with other state-of-the art methods. This developed system provides a more improved and reliable system for driver drowsiness detection with balanced dataset.

Keywords: *drowsiness, vehicle detection, K-Nearest Neighbour (KNN), Random Forest Classifier (RF), Support Vector Machine (SVM).*

INTRODUCTION

Drowsiness is the medical term for excessive daytime sleepiness or weariness. When you are sleepy, it is possible to fall asleep unnecessarily. Even though drowsiness may only linger for a short while, the consequences might be severe. Fatigue is typically the primary factor in drowsiness because it impairs awareness and attention (Cavuoto and Megahed, 2016). However, other elements, such as a lack of focus, specific medicines, sleep disorders, alcohol use, or shift work, can also cause drowsiness. They are unable to predict when they will fall asleep. Even though it is dangerous to doze off while driving, being worn out makes it difficult to do so even when you're awake. According to estimates, one in twenty drivers has fallen asleep behind the wheel. A sudden, unforeseen incident that causes physical harm or property damage as a result of an object's or a person's activity or reaction is referred to as an accident. When the

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driving system of a road vehicle fails to perform one or more duties necessary for the trip to be completed safely, it results in a traffic accident (Ahmed et al., 2022). The Federal Road Safety Corps (FRSC), focusing on Nigeria particularly, states that 22,852 persons were involved in road traffic crashes (RTC) in the fourth quarter of 2022, of whom 1,600 died and 10,232 were injured (FRSC, 2023a, p. 16). Local statistics show that from 2016 to 2021, there were 65,053 traffic fatalities in Nigeria (Jibril et al., 2023). In the context of the frequency of road accidents, the World Bank has placed Nigeria at number 54 globally. With a total length of more than 194,394 km. One of the largest SSA (sub-Saharan Africa) road networks exists in this nation (Yakubu et al., 2023). The majority of these roads were constructed during the effective times of railroads and other alternative land transportation alternatives. However, recent trends in urbanization and car ownership have increased, and in the fourth quarter of 2022, a total of 258,186 new licenses were issued. (FRSC, 2023b).

A deep learning model structure called a convolutional neural network (CNN) is used to handle input having a framework pattern, such as images. Convolutional neural networks are among the most effective forms of deep neural networks for image processing tasks. Convolutional neural networks (CNNs), a kind of deep learning technique, can automatically analyses and find objects in pictures. It is highly efficient and frequently utilized in computer vision applications (Wang et al., 2020). For CNN to produce useful results, large datasets and plenty of processing capacity are required. The most commonly used architectures of convolutional neural network are LeNet (Chao et al., 2019), AlexNet (Kayadibi et al., 2022), ZFNet (Antioquia et al., 2018), GoogLeNet (Anand et al., 2022), VGGNet (Jun, et al., 2018), and ResNet (He, Liu and Tao, 2020)

This paper focuses on the application of an ensemble deep machine learning model for drowsiness detection in vehicle drivers, further emphasizing the use of image- based techniques. The vehicle driver's facial and head sleepiness indicators will be measured using this technique. By observing the drivers' facial features, such as their eyes and mouth, it can identify drowsiness, hence offering a more practical means of resolving the serious problem of driver fatigue

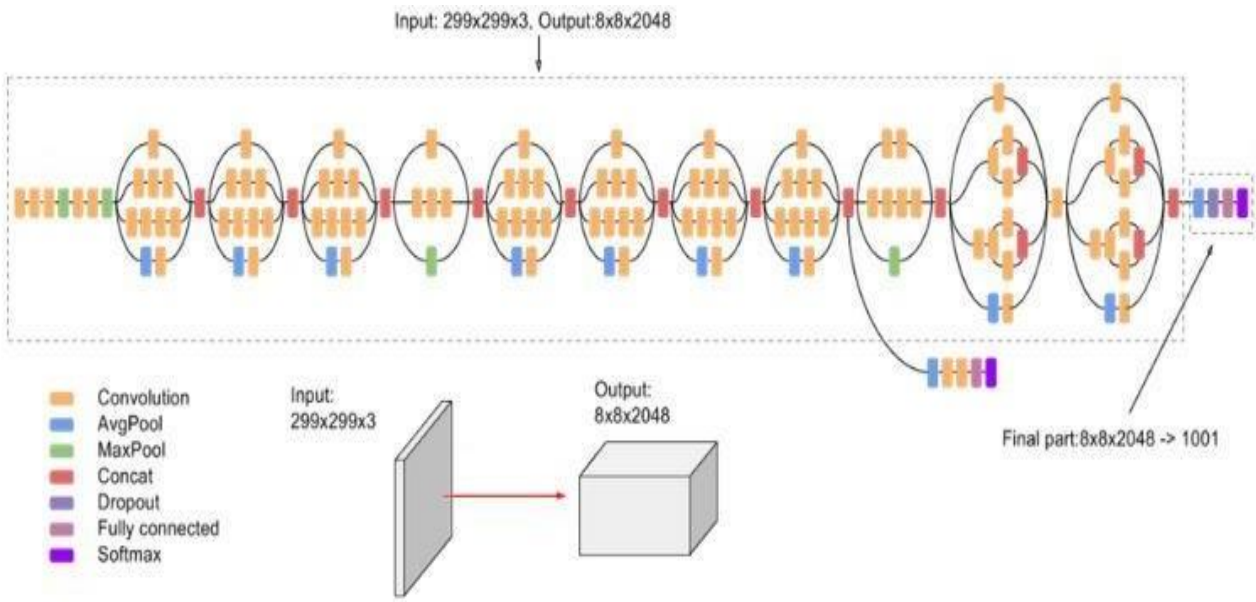

Figure 1: Convolutional neural network architecture (Shahriar, 2023)

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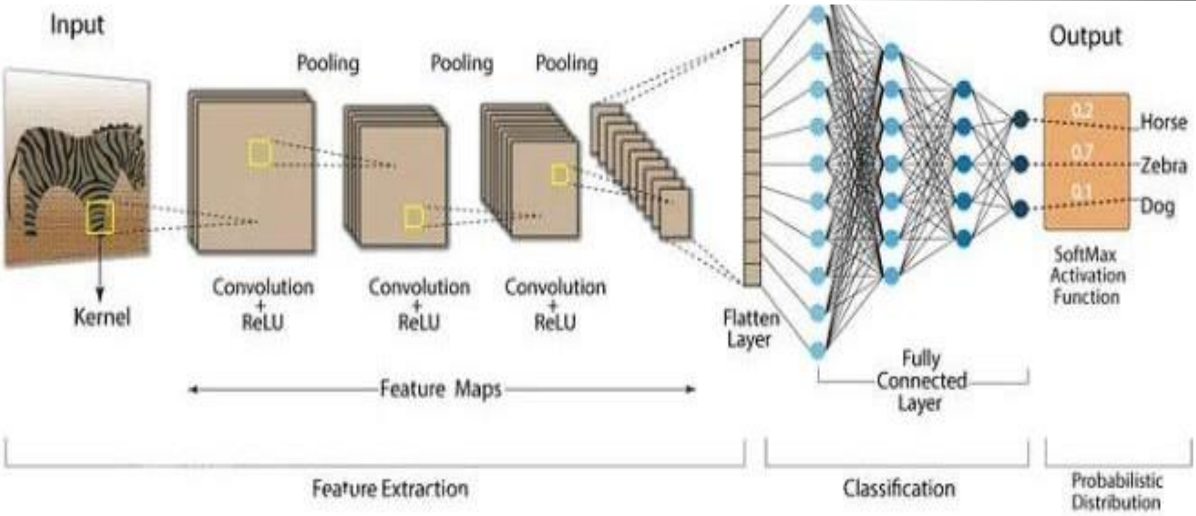

Figure 2: Architecture of Inceptionv3 (Ali*etal*.2021)

METHODOLOGY

The various steps involved in attaining the aim and objectives of the research and providing a block diagram explanation of the driver drowsiness detection system are shown in Figure 3.1. Data gathering, data preparation, picture categorization, and recognition are all parts of the system.

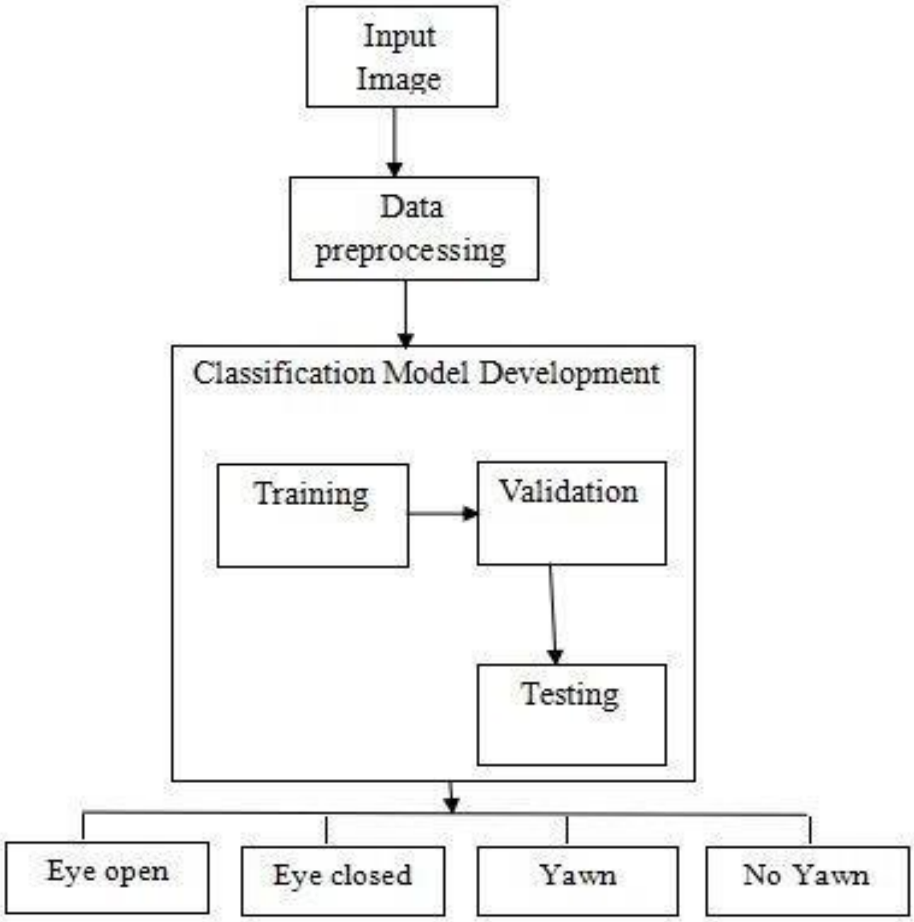

Figure 3: Block diagram of driver drowsiness classification model

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Data Acquisition

The data used for this research is facial images, which is the first step in image processing techniques. Firstly, the data set was acquired locally from various volunteers which involves taking a photograph of their faces and extracting the facial features for easy classification by the system.

Locally Acquired Dataset

This dataset was collected by a broad range of individuals. Each volunteer's facial picture was taken by completing two tasks. The first is by opening the mouth and closing the eyes, while the second is by doing the opposite. These datasets contain images with sizes between 87 and 301KB and sizes between 224 x 224 and 788 x 591pixels. The total number of photographs used in this study is 4000, with 1,000 images included in each of the four classes of the driver sleepiness detection system. Additionally, the model was trained using these. In order to solve the problems with data imbalance, the dataset comprises an equal number of samples for each category (Lin and Jung, 2017).

Even if CNN models are successfully trained using the unbalanced data, the success of driver drowsiness detection in these conditions cannot be ensured by a high degree of accuracy. The model's accuracy will be explored in connection with the study's examination of the impact of balanced datasets. The dataset utilized is summarized in Table1.1. The face image data set sample is shown in Figure 4.

Table1.1: Driver Drowsiness Dataset Description

DatasetName	Format	Classesof Dataset	Range o fImage size	RangeofImagedimension	Numberof Images
Locallyacquired dataset	RGB(jpg)	4	87-301kB	224×224-788×591	4,000

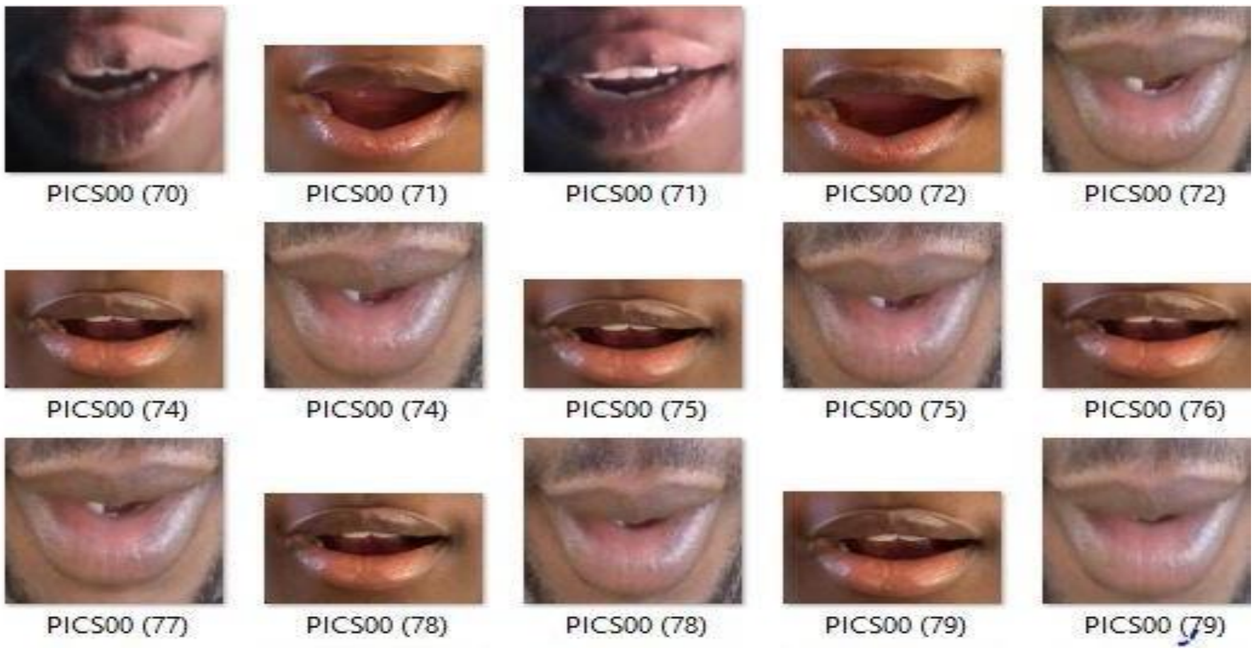

Figure 4: Sample of facial image data set

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Dataset Pre-processing

Image scaling and image filtering are the two procedures used in this study's dataset processing. The driver drowsiness photo dataset comes in a range of sizes; thus, they must be adjusted to fit the requirements of the CNN architectures that have previously been trained. The datasets were reduced in size to 224 × 224 pixels in order to be fed in to the ResNet-50, MobileNetV2, InceptionV3,and MnasNet algorithms.

The model's input, which consists of photos of people with their eyes closed, open, yawning, or not yawning, was scaled down to as size of 224x224 in order to match the input dimensions of the used architectures (Howard *et al.*, 2017). This kind of resizing can also help to simplify computer operations. Because the pixels in the images had varied values, the photos were normalized using a scaling structure called min-max, which ranges from 0 to 1.

Dataset Analysis

A total of 4,000 balanced datasets were separated into four labels in the whole dataset. The dataset's labels each contain 1000 data points. To prevent over fitting, the data samples for each label were divided into 80:10:10 training, validation, and testing groups, respectively.

Table1.2: Illustration of drowsy driver's total images per folder

Classes	Total Number of class	Training set	Validation set	Testing set
Eye open	1000	800	100	100
Eye closed	1000	800	100	100
Yawn	1000	800	100	100
No yawn	1000	800	100	100

The training, validation, and the test set are the three groups into which the acquired dataset is divided. A training dataset is utilized for training a network, and it is during this period that loss values are calculated using forward propagation and learn able parameter updates are made using back propagation. While the training process is being done, the model is assessed, the hyper parameters are adjusted, and the model is chosen using a validation dataset.

When testing the efficacy of a model based on how it performs during the training process with both the validating dataset and the training dataset, it is advised that a test set be used just once at the very last stage of each phase of training a model. Figure 5 displays the folder structure that contains the dataset's breakdown.

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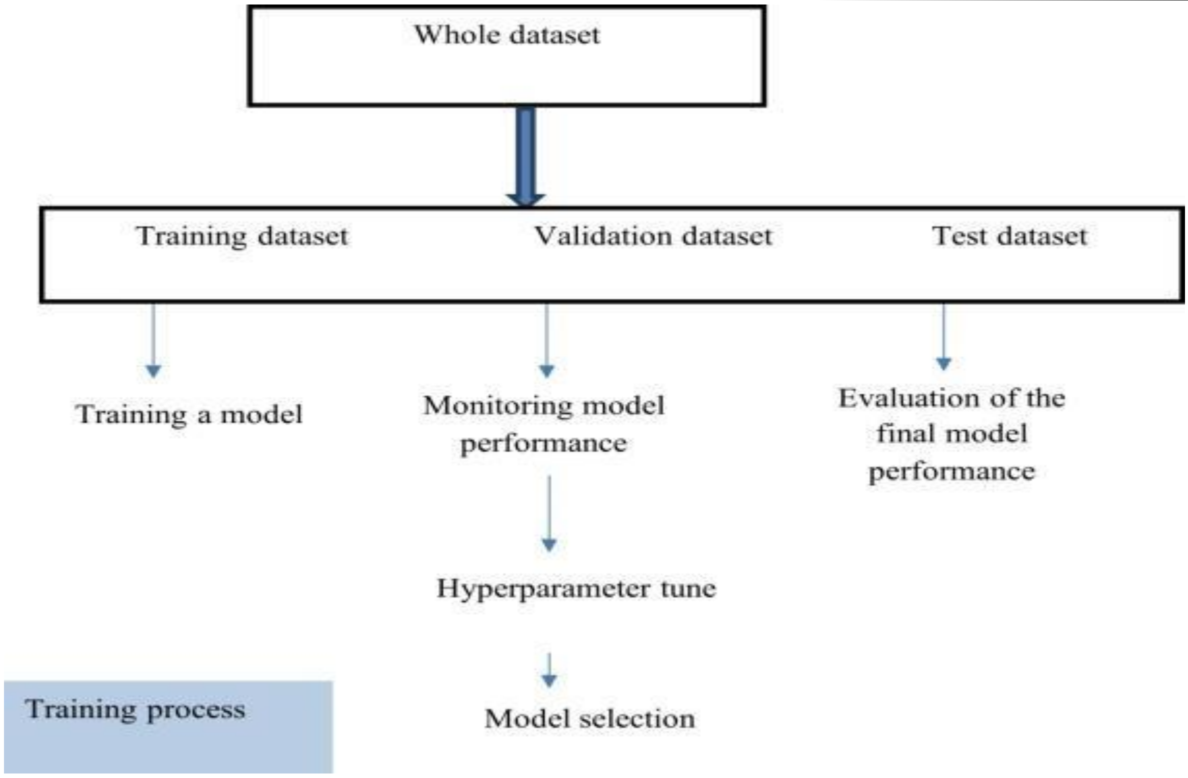

Figure 5: Structure of the data folder for the driver drowsiness detection system

Design of the Ensemble CNN-based Model for Driver Drowsiness Detection

The MobileNetV2, MnasNet, and InceptionV3 architectures serve as the research'sfundamentalmodels.Tensorflowand KeraswereusedalongsidethePythonprogramminglanguageto pre-train the models on the dataset. These models are shallow convolutional neural network lightweight architectures. Over the convolutional layers, additional layers known as the head model were created. For the process of categorizing and preventive analysis, MnasNet, MobileNetV2, and InceptionV3 were used. This is because they have lightweight modalities that enable cheap computing costs and can be easily implemented on embedded systems and mobile devices. Predictive analysis will be utilized to forecast the driver's driving behaviour. The procedure involves employing CNN models to look for patterns that can possibly predict future behaviour.

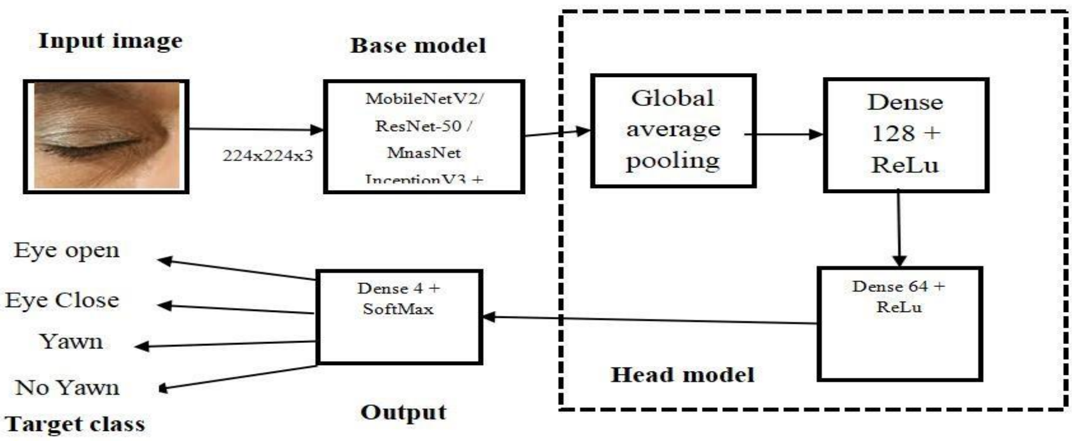

Figure 6: Stages for Driver Drowsiness Detection System

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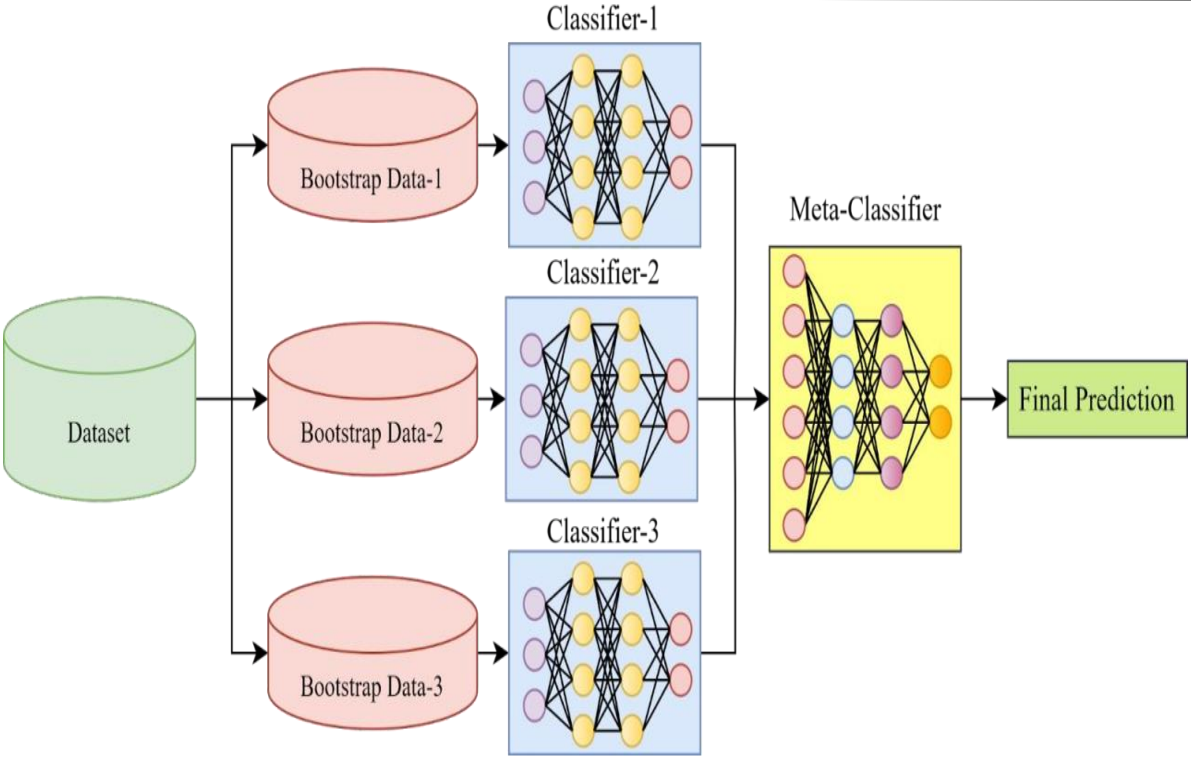

Figure 7: Stacking Ensemble Architecture (Kundu, 2023)

Model Compiling

The driver drowsiness detection system was implemented using python 3.7 as a programming language which is an open source with Scikit-image, Panda, Seaborn, openCV and Scikit-learn libraries to enable it make image manipulation, analysis, visualization and recognition. The TensorFlow Library was implemented to build the model in Python (Abadi*et al.*, 2016).

Additionally, evaluation criteria such as sensitivity, specificity, accuracy, and precision were used to gauge how well the suggested strategy worked. The accuracy measurement is the percentage of items in the testing set that were given the correct category. Equation 3.1 illustrates accuracy's multi-classification. The percentage of real positive cases in a given dataset that have been correctly recognized as having a positive outcome in relation to the total number of positive cases in the test set is what determines a test's sensitivity. By dividing the total number of cases in the testing set that are truly negative by the total number of cases in the dataset that were correctly identified as negative, specificity is calculated. Precision is the proportion of datasets that were correctly classified as positive out of all datasets that the system deemed to be positive.

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$$accuracy = \frac{1}{N} \sum_{k=1}^{/G/} \sum_{x:g(x)=k} I\left(g(x) = \hat{g}(x)\right) \qquad (1)$$

If the classes match, the indicator function I results in 1, otherwise it returns 0.Where I is the indicator function.

To pay closer attention to how each class is performing, a weight w_k Can be assigned to every class such that $\sum_{k=1}^{/G/} w_k = 1$. If the value of w_k Is increased, weighted measure's overall accuracy will be more significantly impacted by observations from that class than from any other class. Equation 2's weighted accuracy will be utilized for computing the factor accuracy:

$$weighted\_accuracy = \sum_{k=1}^{/G/} w_i \sum_{x:g(x)=k} I\left(g(x) = \hat{g}(x)\right) \qquad (2)$$

The models will be evaluated using five criteria. They areas described in Equations 3

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (3)$$

$$Specificity = \frac{TN}{TN+FP} \qquad (4)$$

$$Precision = \frac{TP}{TP+FP}$$

$$Recall = \frac{TP}{TP+FP}$$

$$F1-Score = \frac{2*precision*Recall}{Precision+Recall} \qquad (7)$$

Where "true positive," "true negative," "false positive," and "false negative" are denoted, respectively, by the abbreviations TP, TN, FP, and FN. The model has been verified using the confusion matrix analysis as well (Ruuska *etal.*, 2018). The confusion matrix adds details to the classification model's illustration. Diagonal and off-diagonal elements make up the confusion matrix. The diagonal elements show how many projected labels for a point match actual label, proving thattheclassificationwasaccurate.Thenumberof pointsforwhichtheclassifierincorrectly tagged or misclassified the data is shown as off-diagonal elements. The diagonal numbers of the confusion matrix, which show how accurately the model was able to anticipate specific results, show how precise the predictions were. The Adam optimizer was used to iterate the model, utilizing forward as well as backward propagation (Kingma and Ba, 2014). The model is tuned to detect driver drowsiness thanks to optimized propagation forward and backward iterations.

Adam Optimizer is defined as:

$$\Delta w_t = -\eta \frac{V_t}{\sqrt{S_t + \epsilon}} * g_t \qquad (8)$$

η: Early learning rate
Gt: Gradient at time (t)
Vt: Gradient squares' exponential average
St: Gradient squares 'exponential average

Performance Metrics of the Detection Model

In order to determine the performance of the developed model, the three light weight models used were first trained independently and then collectively. Each was trained using mini-batch gradient descent with a batch size of 32 samples and 10 epochs. An Adam optimizer was employed, and its learning rate decay was adjusted to be equal to the beginning learning rate and inversely proportional to the total number of training epochs. Confusion matrices were utilized to calculate metrics for accuracy, training duration, and loss value in order to assess the performance of the network models andchoosethebestmodelfordrowsinessdetection.Themodel'sperformancewascompared using a number of criteria, such as accuracy, F1-score, and recall

Table 1.3: Ensemble loss and accuracy function

Epoch	Loss	accuracy	val loss	Val accuracy
1	0.1088	0.9947	0.3445	0.9025
2	0.1052	0.9959	0.3271	0.9175
3	0.0871	0.9959	0.3575	0.9075
4	0.1552	0.9944	0.3495	0.9325
5	0.1427	0.9950	0.3534	0.9325
6	0.1380	0.9947	0.3580	0.2950
7	0.1393	0.9941	0.3482	0.9175

Table 1.4: Result of training with Ensemble

Dataset	Precision	Recall	F1-score	Support
Closed	0.86	0.95	0.90	91
Open	1.00	0.86	0.93	116
Noyawn	1.00	0.88	0.93	114
Yawn	0.79	1.00	0.88	79

The ensemble model's testing accuracy is 91.25%. Because each measure yields a different value based on the model used, each needs a different training component. Using this model, the callback was initiated at epoch 7 of the dataset training phase because accuracy had not improved further .In contrast, the ensemble model confusion matrix for identifying drowsy drivers is shown in Figure 4.1. Since it can categorize any distribution and has dependable data linkages, which enable it to provide the TP, FP, and FN for the model validation, its use was taken into account. It also offers further details regarding the accuracy of the model.

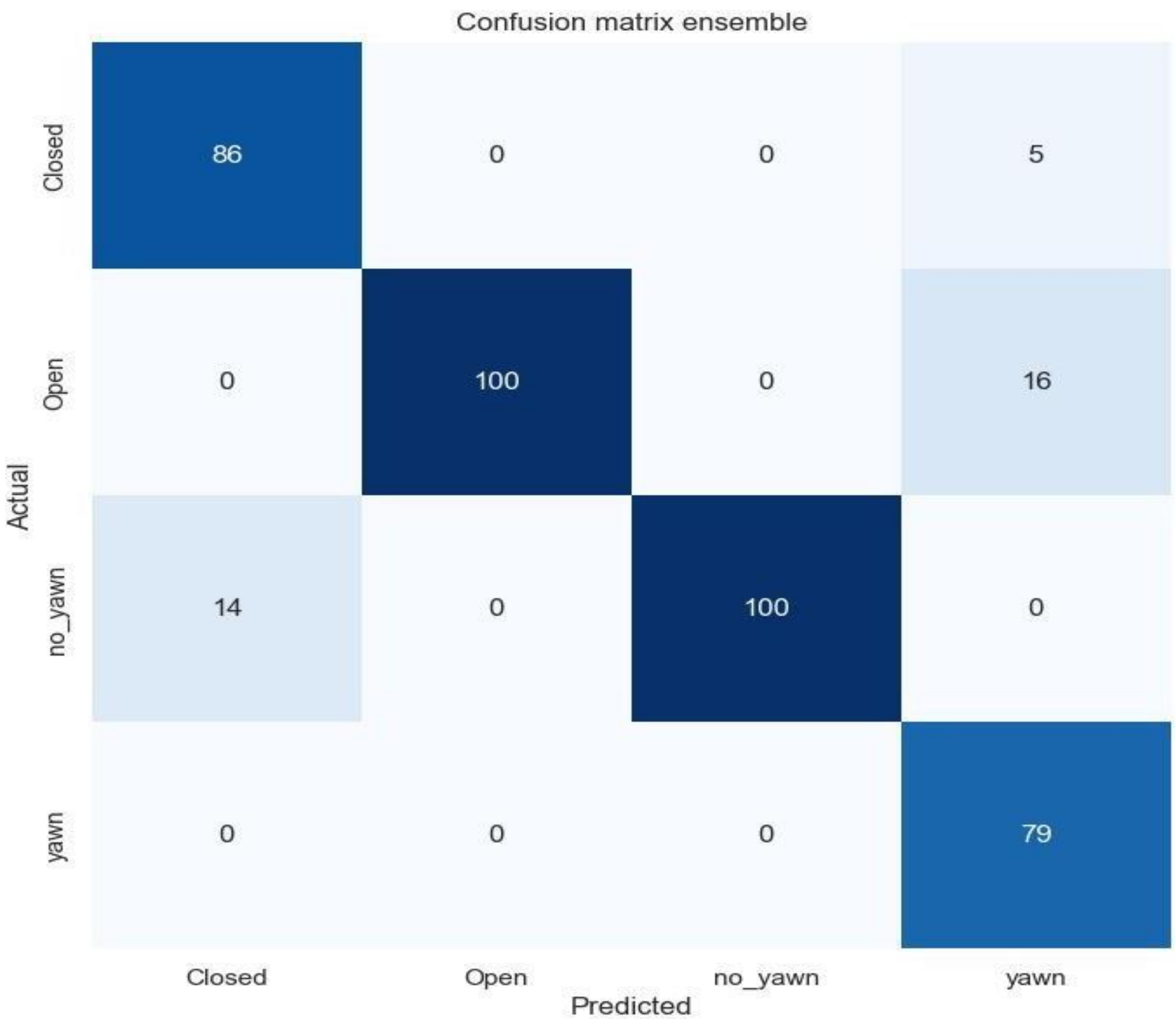

Figure 8: Confusion matrix of the ensemble model for driver drowsiness detection

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Figure 8 displays the confusion matrix for the ensemble model. The diagonal line of the training dataset displays the objects that were correctly classified. The eye-closed class has a true positive number (TP) of 86 and a true negative number (TN) of 14, which is incorrectly classified as no yawn. With a true positive (TP) rating of 100, the responses in the Eye Open (open) category were rated perfectly. For the no yawn classes, there is no genuine negative value and a true positive value of 100. Finally, the true negative (TN) values for the yawn category are 5and 16, respectively, whereas the actual positive (TP) value is 79. The classification of these numbers as eye-open and eye-closed was done wrongly. The validation and training accuracy and loss for the ensemble model's detection of tired drivers are displayed in Figures 8 and 9, respectively.

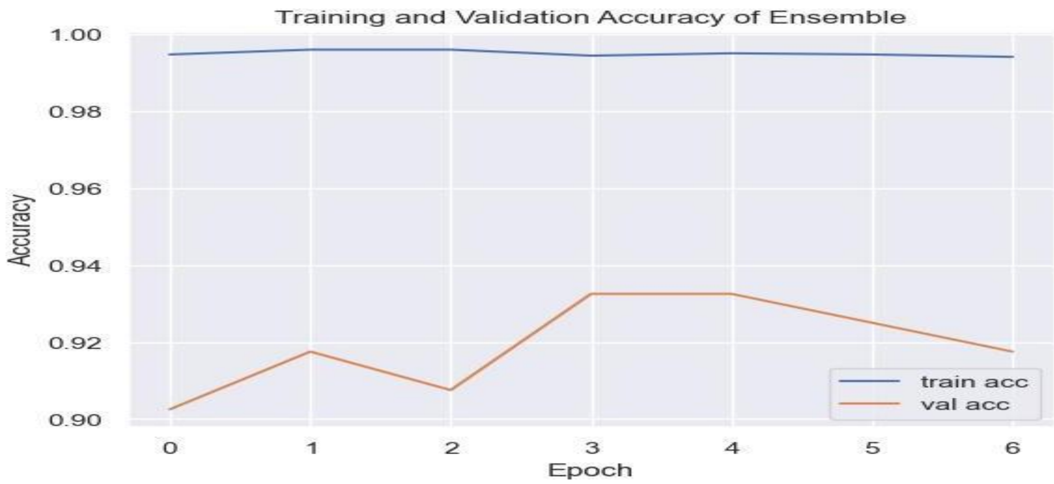

Figure 9: Plot of ensemble for the training and validation accuracy

As seen by the plot diagram in Figure 9, the model was trained to generate the best reading at epoch 2 with an accuracy of 0.9959 using the locally accessible dataset. According to the plot diagram above, the accuracy increases at regular intervals, beginning at epoch 1 and continuing until it reaches the final epoch, which signifies the end of the iteration. The model's validation accuracy starts to rise at epoch 1 at 0.9025; it then increases over a predetermined period of time, peaking at 0.9325 atepoch4. Before the call-back function is activated, it then decreases to 0.9175 at epoch7.

Figure 10: Plot of ensemble for the training and validation loss

The plot diagram of the loss is displayed at different epochs in Figure 10. The model's loss value drops for the first step's training set. At epoch 1, the loss value was1.1088, and it decreased gradually until the last epoch, at which point the call back function was triggered. Up to epoch 7, when the call-back function was triggered because it was no longer able to provide a lower value, the validation set loss valuewas0.3445 at epoch1.

Discussion of Results

In this study, a convolutional neural network-based model for detecting drowsiness in vehicle drivers was developed. The developed model consists of three light weight CNN architectures, which are MnasNet, MobileNetV2, and InceptionV3, which are assembled using the stacking method. The vehicle driver's drowsiness problem has been a major factor in traffic accidents all over the world. The performance of the model was assessed using various parameters like precision, F1 score, recall, accuracy, and the confusion matrix. The ensemble CNN-based model produces an accuracy of91.25%, the average precision score is 91%, the average recall is 92.25%, and the average F1 score is 91.63%, which shows that it can identify fatigued vehicle drivers.

Table1.5: Performance Evaluation and Comparison of Some Selected CNN Models.

S/N	**Algorithm**	**Accuracy (%)**	**F1-Score (%)**	**Precision (%)**	**Recall (%)**
1	MobileNetV2	82.25	83.10	87.00	82.40
2	MnasNet	70.75	70.90	73.50	70.90
3	InceptionV3	80.25	80.60	85.20	80.40
4	Developed model	91.25	91.63	91.00	92.25

Comparison of the Developed System with Existing Systems for Vehicle Drivers Detection

The performance of the developed vehicle driver system was compared with some of the existing systems. Vijayan and Sherly (2019) used a deep learning approach on the National Tsing Hua University (NTHU) Drowsy Driver Detection video dataset. The research uses three CNN models. The test's average accuracy results for VGG16 are71.25%, ResNet50is 76.14%, InceptionV3 is78.45%, andFFAis75.58%.

Aghera et al. (2020) use the MnasNet model with the FER2013 dataset to tackle the problem. After utilizing a batch size of 32 and resizing the photos to 224x224 pixels, the accuracy for the study was 70.82%. Table 1.6 below indicates the comparison of the developed vehicle driver detection system with some existing systems.

Table1.6: Comparison to the Developed Vehicle Drivers Detection System with some Existing systems.

S/N	**Authors**	**Dataset**	**Classifier**	**Accuracy**
1	Vijayan andSherly (2019)	TNTHU	InceptionV3,ResNet50,VGG16, FFA	78.45%, 76.14%, 71.25%, 75.58%.
2	Aghera et al.(2020)	FER2013	MnasNet	70.82%
3	Developed DDD system	Locally acquired Dataset	Ensemble CNN-based light weight model	91.25%

CONCLUSION

This study has developed a vehicle driver drowsiness detection system using a locally acquired dataset. A CNN-based model was developed. Python programming was used to build the driver sleepiness detection system on Google Co lab, which is a hosted Jupyter notebook platform. The dataset was gathered locally, specifically for the purpose of this study. There are 4,000 photos in all. For improved efficiency, the locally obtained datasets were further split into four separate classes. The four classifications are, according to order: no yawn, yawn, eye closed, and eye open. The four classes developed in this work will aid in the enhancement of driver sleepiness detection capabilities and also offer a clearer understanding of the use of multiclass classification as opposed to simple binary classification, as suggested by Balam *et al*. (2021).

To address the data inconsistency issue, which Meneses *et al*. (2023) recognized as a common issue, 1,000 photos were randomly assigned to each dataset image. The data architecture underwent retraining to identify sleepy eyes and yawning as signs of inattentive driving. Early detection of drowsy drivers is crucial; thus, the classifier will improve the efficacy and accuracy of the current driver drowsiness detection system and the ease of deployment on embedded systems and mobile devices. The use of pre-trained networks without GPU support is a crucial aspect of this research because deepnet works were tuned for it. Using the pre-trained networks, deep features were effectively retrieved from the dataset. The performance of the developed system was assessed, and the results showed that it might be enhanced.

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