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A Hybrid Approach To Real-Time Fatigue Monitoring In Drivers

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ABSTRACT

Driven by exhaustion is one of the leading causes of road accidents across the world which result in many reported deaths each year. This project attempts to mitigate the challenge using machine learning and deep learning techniques for easier and precise detection of fatigue. EEG signals and video images from the DROZY dataset are utilized to train ML and DL models, respectively. SVM, Random Forest, and KNN are some of the machine learning algorithms utilized for the analysis of EEG signals while the images are analyzed through CNN, ConvLSTM, and also a multi-model approach CNN+ConvLSTM. Further accuracy is enhanced by employing ensemble techniques such as Bagging Classifier. PV and PCA methods were applied to obtain superior model performance resulting in all 100% accuracy for all CNN-based approaches. Thus, this system provides strong approaches toward supporting real time driver fatigue assessment.

Keywords: ConvLSTM, EEG, KNN

INTRODUCTION:

With the rise in the number of road traffic accidents due to driving while being tired, manufacturers of automobiles have seen a requirement to shift their focus in the development of systems that help to monitor and improve the overall road safety. A multi-faceted approach using the Internet of Things together with embedded systems, smartphone applications, cloud computing, and centralized data processing is the modern approach that has been adopted. Fatigue detection techniques can be classified into behavioral-based methods, vehicle-based methods, and physical-based methods.

The techniques described in this study, including eye and head movement and other facial expressions, make use of computer vision and image processing to identify factors that may compromise alertness of a driver. The techniques vehicle-based whereby embedded sensors in the vehicle sense steering wheel angles and movements, hand position relative to wheel and deviation from lane center. The physical approach is via devices which are worn and record physiological signals, for example, some EEG, ECG and EOG devices which measure heart rate, respiratory rate and even the activity of the brain.

Some of these approaches with a few modifications can provide a complete framework for the prevention of accidents caused as a result of the gradual deterioration in driver performance caused by fatigue.

GAP IDENTIFIED BASED ON LITERATURE SURVEY:

From the extensive literature review done on driver fatigue detection, there are still key gaps that need to be addressed. Pioneering research did just that creating techniques able to detect fatigue but only with EEG signals or only with image data which is not robust enough. In this day and time such techniques are inappropriate due to the diversity of driving conditions as well as the behavior of the great number of the drivers involved.

Most of the previous works are focused on single algorithms already developed which either do not include all the strengths of both ML and DL or do not apply them alongside each other. Failure to channel the relevant which made the methods efficient such as PCA techniques during full feature extraction greatly reduces the efficiency of approaches. Also, the majority of the systems did not test the applicability of ways in which the accuracy can be improved by the use of ensemble methods.

This project solves these gaps by focusing on images and EEG (duel modality) with better pre-processing techniques and with the use of hybrid along with ensemble classifiers. As a result, Together these enhancements provide a better, more scalable and more efficient real time approach to fatigue monitoring in driver’s supervisory systems.

PROBLEM STATEMENT:

Driver fatigue could be considered one of the major reasons for negligent driving which causes fatal road accidents across the world. Algorithms that are already developed to detect fatigue often do not perform with enough accuracy and strength.

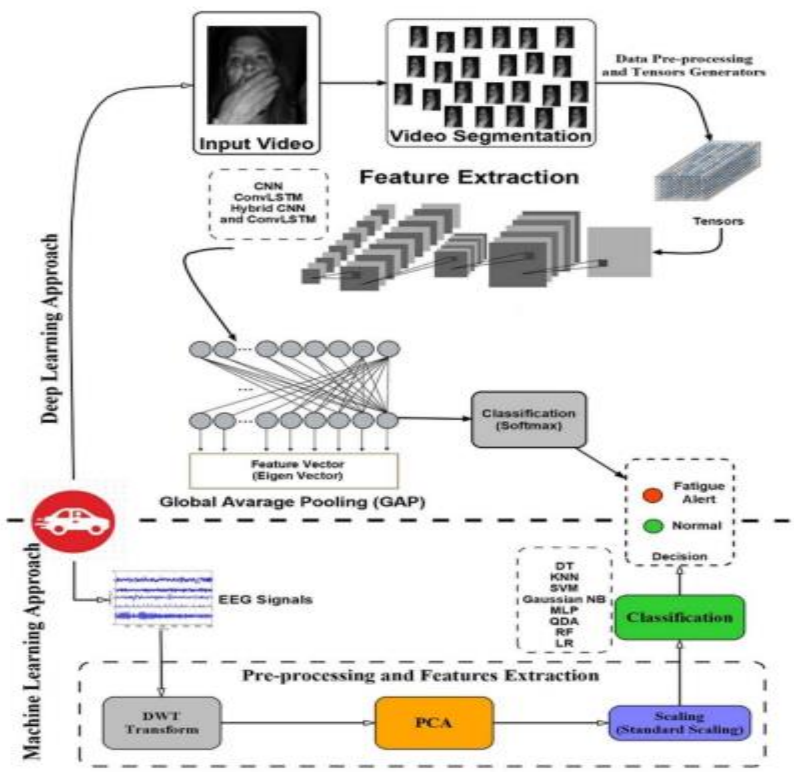
Key Challenges:

- • Data Variability: Data variation in subjects' EEG signals and image data affects the generalization of the models.
- • Real-Time Analysis: Developing a system prediction that doesn't sacrifice accuracy.
- • Feature Selection: Selection of important features from large feature datasets in order to enhance the performance of the models.
- • Algorithm Optimization: Adjusting Parameters of the ML and DL algorithms to be adaptable to different environmental circumstances and driving conditions.
- • Scalability: Making the system robust enough to work with different type of datasets and datasets as well.

PROPOSED METHOD:

The proposed system is effective in the detection of the driver's fatigue as it combines the capabilities of deep and machine learning. ML models include SVM, Random Forest, Naive Bayes which are used to classify states of fatigue based on the EEG signal data. At the same time, the fatigue states are also being recognized from video images using deep learning models including CNN, and ConvLSTM, and a hybrid model of both CNN and ConvLSTM to improve accuracy. Hyperparameter adjustment is supported with Grid Search, and PCA features are also employed. For training and evaluation, the DROZY dataset is used and in addition, the performance of the ML models is enhanced by an ensemble Bagging Classifier. This way, the system is able to provide the user with an accurate fatigue detection and prevention. Such a system is a perfect and effective way to curb road accidents that are due to negligence on the part of the driver.

ARCHITECTURE:



DATASET:

This project uses the DROZY dataset which contains EEG signal and video images. The EEG Signals measure brain activity and knowing the brain activity assists to better understand the alertness or fatigue of the driver. The dataset has labeled instances of active and fatigued states in order to make the training of the machine learning models complete. Video images are part of the datatset allowing the deep learning algorithms to capture driver's facial expressions and behaviors that could indicate fatigue. This multi modal dataset ensures that even with the variability and complexity of fatigue detection in real life, the model training will be successful.

METHODOLOGY:

Data Collection:

Employ the DROZY dataset EEG signals and video images that have been tagged for active and fatigued states.

Preprocessing:

Standardize and remove noise from EEG signal data by using Normalization.

Dimensionality reduction with feature selection using PCA approach.

Resize and augment images for thorough model training.

Machine Learning Model Development:

Use EEG data to model SVM, KNN, Random Forest, Decision Tree, Logistic Regression, Naïve Bayes using EEG data.

Hyperparameter tweaking is done via Grid Search for performance metrics including accuracy and precision to be achieved.

Deep Learning Model Development:

Video images are analyzed with CNN models and ConvLSTM models.

To devise a hybrid model for spatial and temporal analysis tasks by merging CNN and ConvLSTM together.

Model Evaluation:

The performance of ML models will be assessed using accuracy, F1 score, and confusion matrix among others.

For validation of DL models, accuracy and loss metrics will be the key metrics for evaluation.

Making comparison of the performance of models in order to be able to identify the best performing one.

Ensemble Learning:

Incorporate Bagging Classifier in order to enhance performance of the system by combining results from several ML algorithms.

Integration and Testing:

At this stage, ML and DL predictions will be integrated and it will provide the final output.

The integrated system will be evaluated and tested with real time data to test how robust the model is.

Performance Visualization:

Graphs, confusion matrices and ROC curves with different models will be used to visualize the results and accuracy level.

EVALUATION:

Precision:

Formula: $\text{Precision} = \frac{\text{True Positives}}{\text{True Positives}+\text{False Positives}}$

Recall (Sensitivity):

Formula: $\text{Recall} = \frac{\text{True Positives}}{\text{True Positives}+\text{False Negatives}}$

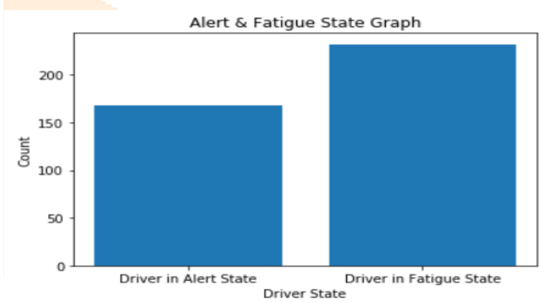
F1 Score:

Formula: $F1 = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}}$

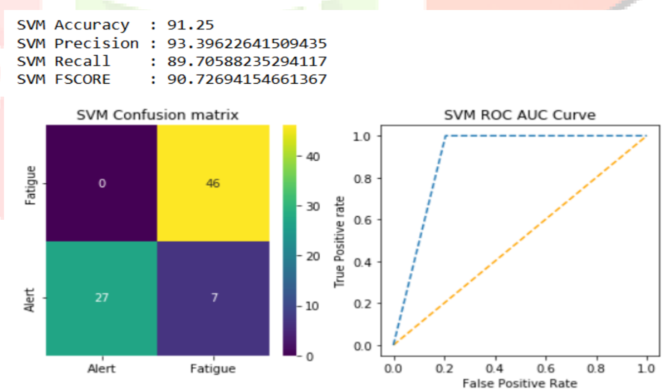
Accuracy:

Formula: $\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}}$

RESULTS:

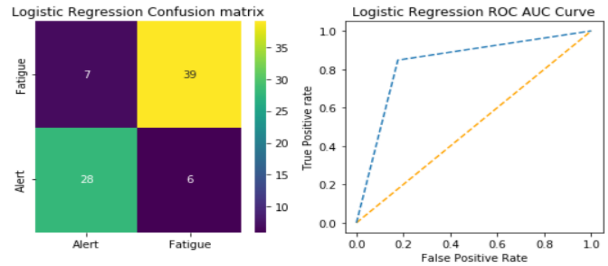


In above screen we are finding and plotting number of Active and Fatigue records found in dataset



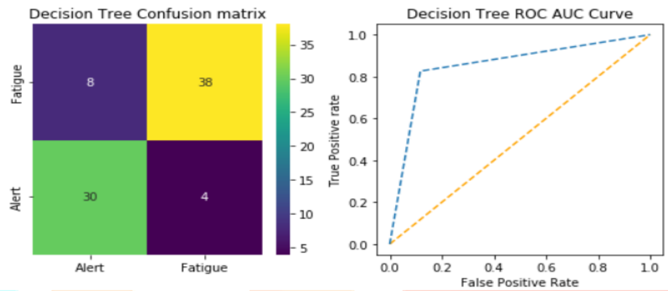
SVM with Grid parameters tuning and we got accuracy as 91%

```
Logistic Regression Accuracy  : 83.75
Logistic Regression Precision : 83.33333333333334
Logistic Regression Recall    : 83.56777493606138
Logistic Regression FSCORE    : 83.4368530020704
```



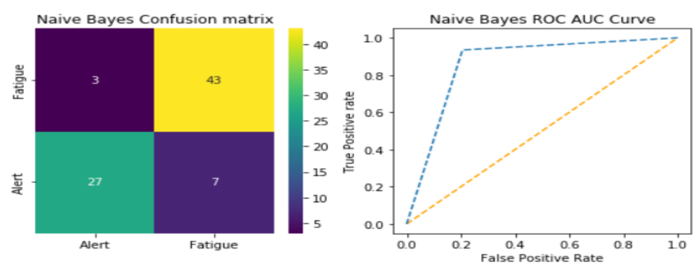
In above screen logistic regression got 83% accuracy

```
Decision Tree Accuracy  : 85.0
Decision Tree Precision : 84.71177944862156
Decision Tree Recall    : 85.42199488491049
Decision Tree FSCORE    : 84.84848484848484
```



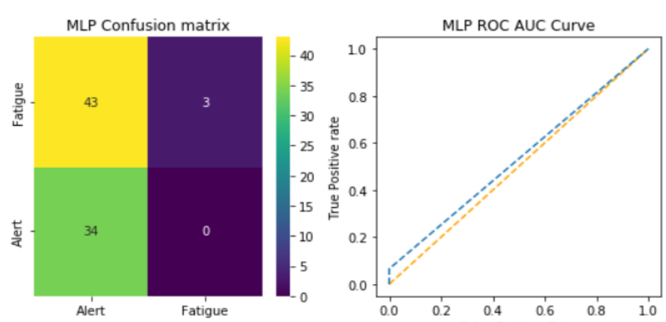
In above screen decision tree got 85% accuracy

```
Naive Bayes Accuracy  : 87.5
Naive Bayes Precision : 88.0
Naive Bayes Recall    : 86.44501278772378
Naive Bayes FSCORE    : 86.97916666666667
```



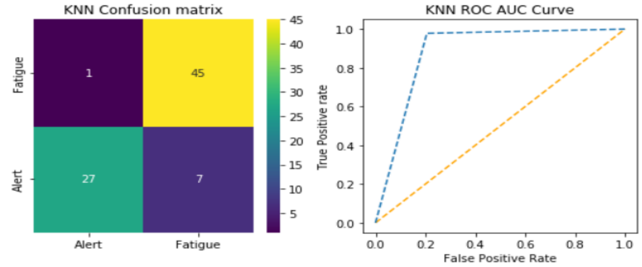
In above screen Naïve Bayes got 87% accuracy

```
MLP Accuracy  : 46.25
MLP Precision : 72.07792207792207
MLP Recall    : 53.2608695652174
MLP FSCORE    : 36.753079610222464
```



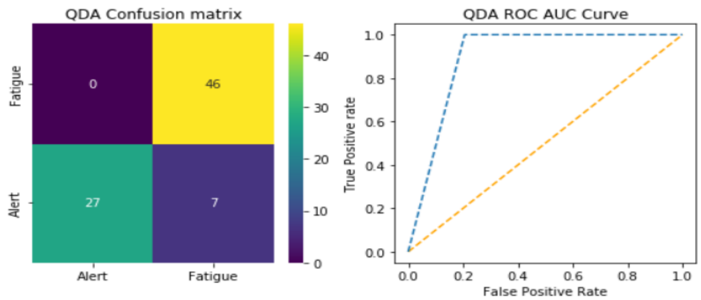
In above screen MLP got 46% accuracy

```
KNN Accuracy  : 90.0
KNN Precision : 91.4835164835165
KNN Recall    : 88.61892583120205
KNN FSCORE    : 89.46675444371297
```



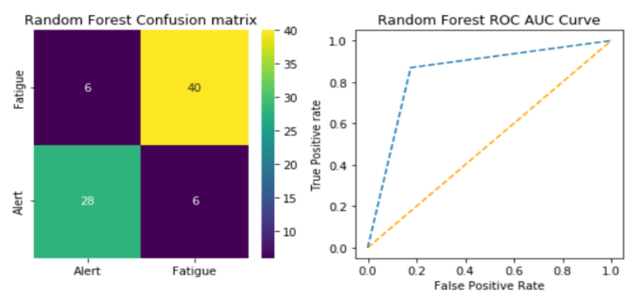
In above screen KNN got 90% accuracy

```
QDA Accuracy  : 91.25
QDA Precision : 93.39622641509435
QDA Recall    : 89.70588235294117
QDA FSCORE    : 90.72694154661367
```



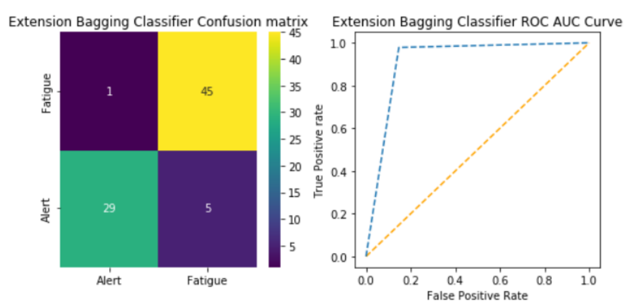
In above screen QDA got 91% accuracy

```
Random Forest Accuracy  : 85.0
Random Forest Precision : 84.65473145780051
Random Forest Recall    : 84.65473145780051
Random Forest FSCORE    : 84.65473145780051
```

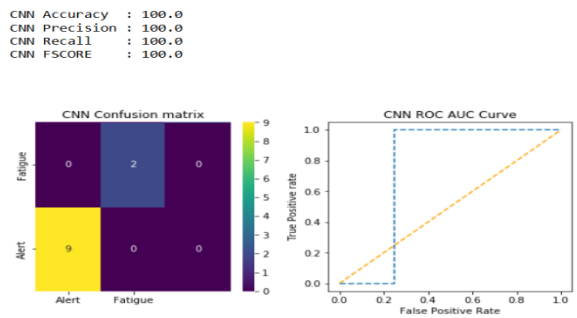


In above screen Random Forest got 85% accuracy

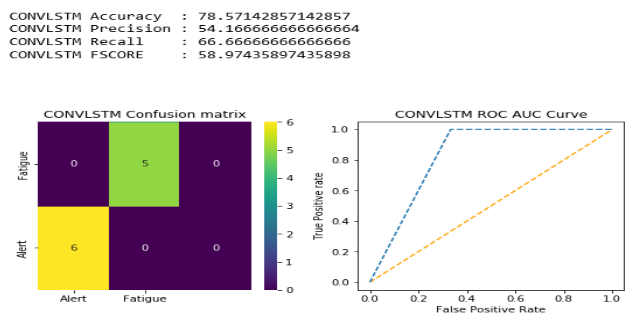
```
Extension Bagging Classifier Accuracy  : 92.5
Extension Bagging Classifier Precision : 93.33333333333333
Extension Bagging Classifier Recall    : 91.56010230179028
Extension Bagging Classifier FSCORE    : 92.1875
```



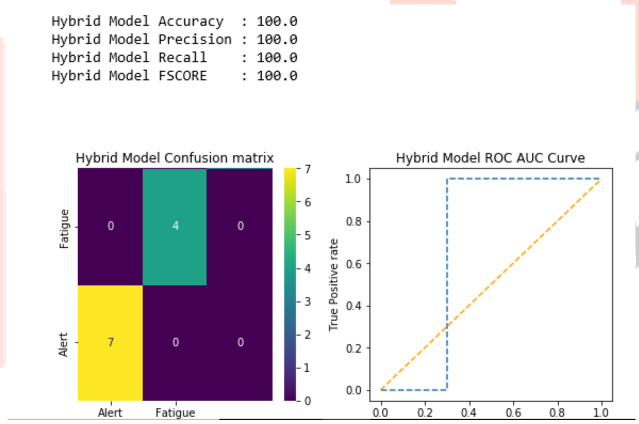
Bagging classifier got 92.5% accuracy



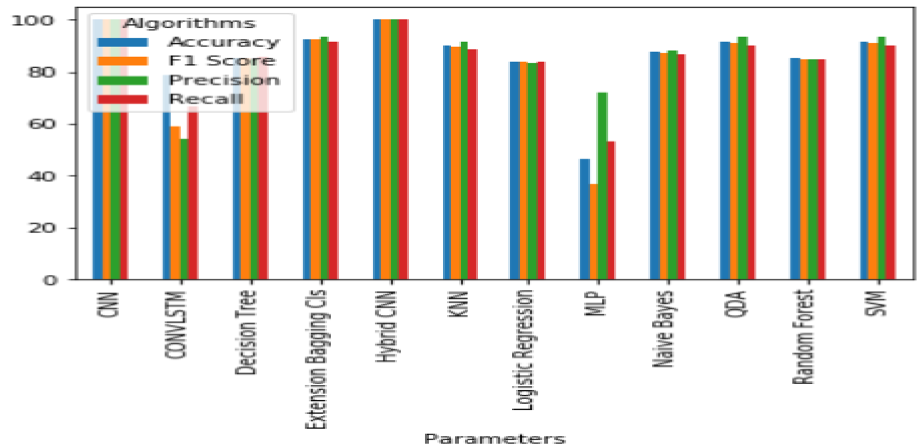
In above screen with CNN we got 100% accuracy



In above screen with CONVLSTM we got 78% accuracy



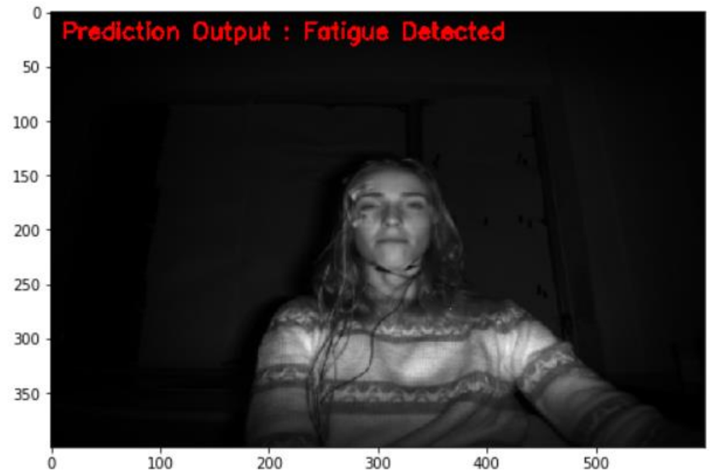
In above screen Hybrid CNN model got 100% accuracy



In above screen for all algorithms we are plotting accuracy and other metrics graph where x-axis represents algorithm names and y-axis represents metric values

	Algorithm Name	Precison	Recall	FScore	Accuracy
0	SVM	93.396226	89.705882	90.726942	91.250000
1	Logistic Regression	83.333333	83.567775	83.436853	83.750000
2	Decision Tree	84.711779	85.421995	84.848485	85.000000
3	Naive Bayes	88.000000	86.445013	86.979167	87.500000
4	MLP	72.077922	53.260870	36.753080	46.250000
5	KNN	91.483516	88.618926	89.466754	90.000000
6	QDA	93.396226	89.705882	90.726942	91.250000
7	Random Forest	84.654731	84.654731	84.654731	85.000000
8	Extension Bagging Classifier	93.333333	91.560102	92.187500	92.500000
9	CNN	100.000000	100.000000	100.000000	100.000000
10	CONVLSTM	54.166667	66.666667	58.974359	78.571429
11	Hybrid CNN	100.000000	100.000000	100.000000	100.000000

In above screen in tabular format we are displaying all algorithms performance and in ML algorithms we can see Extension Bagging got high accuracy



Prediction driver behaviour as Active or Fatigue

CONCLUSION

In conclusion, this advanced approach combining, machine learning and deep learning, effectively handles the increasing challenges of driver fatigue detection due to the usefulness of the EEG signals and video images as a combined approach in fatigue identification. Using the DROZY dataset, along with rigorous pre-processing methods and optimized models, the system gets a very high accuracy, where the hybrid and CNN models even reach an accuracy of 100%. The performance is in addition improved by the use of ensemble methods explaining the suitability of developing systems that will be real-time in their usage and relevant in traffic safety. This new integrated model is comprehensive and extended, thus useful in and can be used to effectively reduce driver-induced negligence related road accidents and sets a new standard for future systems aimed at fatigue detection.

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