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## An Enhanced Early object Detection of Driver Drowsiness Using supervised Machine Learning approach by comparing SVM over Random Forest

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**Keywords:** [driver drowsiness](https://www.mdpi.com/search?q=driver%20drowsiness), [machine learning](https://www.mdpi.com/search?q=machine%20learning), SVM, sleepiness, accuracy, detection, physiological conditions, road traffic accidents.

**ABSTRACT**

**Aim**: The aim is an enhanced early object detection of driver drowsiness using machine learning by comparing supervised Machine learning techniques by comparing SVM over random forest. **Materials and Methods**: In this Project, we have used two algorithms such as SVM and random forest. In an age where advancement of self-driving or automated cars were increasing, for assuring the safety of passengers was more significant than earlier. This is often very true when the passenger or driver isn't able to drive and helps in reducing the most road traffic accidents. The mean accuracy of the present research has been calculated under supervised learning with 0.8 as the alpha value, a G-Power value of 0.8, and CI of 95%. **Result**: After doing this research, the Novel SVM has attained an accuracy of 97.70% and the random forest algorithm has achieved an accuracy of 91.20%. An Independent samples T-Test analysis has been executed, and its significance value is found to be p=.670 (p<0.005), suggesting statistical significance. **Conclusion:** In the present research, the Novel SVM algorithm is collated with the Random Forest algorithm. After performing the current research experiment, the Novel SVM algorithm has been found to have more perfection than the Random Forest.

**Keywords:** [driver drowsiness](https://www.mdpi.com/search?q=driver%20drowsiness), [machine learning](https://www.mdpi.com/search?q=machine%20learning), Novel SVM, sleepiness, accuracy, detection, physiological conditions, road traffic accidents.

**INTRODUCTION**

Drowsy driving is one of the primary reasons for road traffic accidents. Since drivers could not react to dangerous situations when drowsy, major road traffic accidents can occur. To prevent road traffic accidents due to drowsy state driving, it is efficient for face detection of driver drowsiness early and accurately [(De, Bhattacharyya, and Dutta 2018)](https://paperpile.com/c/gihtuk/NJFF).Past investigations showed that the sleepiness level of a driver is connected with their look, driving practices, and physiological conditions[(Picot, Charbonnier, and Caplier 2008)](https://paperpile.com/c/gihtuk/Hvi0). There is a solid relationship between genuine tiredness and emotional assessment in view of looks [(Liu et al. 2010)](https://paperpile.com/c/gihtuk/Iuz1).Drowsiness is identified by using vision-based techniques like eyes detection, yawning, and nodding. When it comes to yawning and nodding some people can sleep without yawning and nodding. Various studies have suggested that around 20% of all road accidents are fatigue-related, up to 50% on certain roads. Some of the current systems learn driver patterns and can detect when a driver is becoming drowsy.Driver attention monitoring identifies any reduction in driver alertness[(Dinges and Grace, n.d.)](https://paperpile.com/c/gihtuk/9uGK). Using an infrared camera above the steering wheel, driver attention monitoring continuously monitors: the eyes for signs of tiredness (blinking); the face and head movements for signs of distraction; and the course steered by the car in its road lane (deviations or steering movements by the driver).Hence, checking a driver's looks is a broadly acknowledged strategy for recognizing driver sleepiness which helps in reducing road traffic accidents [(Borghini et al. 2014)](https://paperpile.com/c/gihtuk/1Rid).

The research papers are collected from the last 5 years i.e., 2018-2022 and almost 300 research articles have been reported in “IEEE Xplore '' and all over 390 research papers are published in the “Science Direct '' on driver drowsiness. The IEEE Explore and ScienceDirect are considered as the main databases in collecting the research papers for this research experiment. Observing head position, eye squints, and body development (Y. Yin, Y. Xio 2010) has likewise been utilized to recognize driver sluggishness [(Seifoory et al. 2011)](https://paperpile.com/c/gihtuk/ofRW). What's more, physiological conditions are broadly used to identify driver sleepiness since it straightforwardly mirrors the inward physiological conditions of drivers in helping to reduce road traffic accidents.This work compares the Random Forest algorithm for early object detection of driver drowsiness[(Jap et al. 2009)](https://paperpile.com/c/gihtuk/Eli3). In 2007, [Volvo Cars](https://en.wikipedia.org/wiki/Volvo_Cars) launched the world's first Driver Drowsiness Detection system, Driver Alert Control. The system monitors the car's movements and assesses whether the vehicle is being driven in a controlled or uncontrolled way. If the system detects a high risk of the driver being drowsy, the driver is alerted via an audible signal[(Danisman et al. 2010)](https://paperpile.com/c/gihtuk/cpos). Also, a text message appears in the car's information display, alerting him or her with a coffee cup symbol to take a break. Additionally, the driver can continuously retrieve driving information from the car's trip computer. The starting-point is five bars. The less consistent the driving, the fewer bars remain. Using the Novel SVM model with Random Forest technique for early object detection of driver drowsiness and physiological conditions using machine learning [(Bhattacharyya et al. 2018)](https://paperpile.com/c/gihtuk/PZJL). The Novel SVM is likewise generally utilized for grouping as an administered learning strategy. It hopes to enhance a value known as the edge, which is described as the distance between as far as possible and the closest planning test to as far as possible[(Victor, Lee, and Regan 2013)](https://paperpile.com/c/gihtuk/x2xg).

RF is an outfit of the choice tree models. It is a machine learning technique which has speculation properties and runs productively on enormous data sets[(Kim and Shin 2014)](https://paperpile.com/c/gihtuk/k6Ft). Besides, it computes the significance of elements. The consequences of the past review showed that the RF calculation can acquire roughly 80% precision while characterizing the alarm and somewhat sleepiness state [(McKnight 1998)](https://paperpile.com/c/gihtuk/5JPk). Suppose there is a dataset that contains multiple face images. So, this dataset is given to the Random forest classifier. The dataset is divided into subsets and given to each decision tree[(Welsh, Ashikhmin, and Mueller 2002)](https://paperpile.com/c/gihtuk/7VRe) . During the training phase, each decision tree produces a prediction result, and when a new data point occurs, then based on the majority of results, the Random Forest classifier predicts the final decision[(Foster et al. 2020)](https://paperpile.com/c/gihtuk/ltIe).It is used for classification and regression tasks due to its high accuracy, robustness, feature importance, versatility, and scalability[(Suthaharan 2015)](https://paperpile.com/c/gihtuk/UkBL). Random Forest reduces overfitting by averaging multiple decision trees and is less sensitive to noise and outliers in the data. To examine the execution of the grouping framework, we likewise assessed the exhibition of characterization not just utilizing full crossover measures (vehicle-based, conduct, and physiological conditions) yet additionally utilizing half and half measures without physiological conditions, sleepiness measures, as these are viewed as more challenging to carry out than different measures which helps in road traffic accidents([(Chowdhury et al. 2018)](https://paperpile.com/c/gihtuk/jjFK)

**MATERIALS AND METHODS**

The current experimentation work has been carried out in the Machine Learning Laboratory at Saveetha School of Engineering, Saveetha Institute of Medical And Technical Sciences (SIMATS), Chennai. The dataset for this particular research study was sourced from the driver drowsiness and generated using software with various samples.

The database is set up so that testing takes up 25% of its space, while 75% of it is used for training. Two sets are used, and each set has 10 data samples, for a total of twenty samples that are taken into account. The Novel SVM algorithm was used in Group I, and Random Forest algorithm was used in Group 2. The implementation makes use of Python software. The G power was set at 80%, the confidence interval was set at 95%, and the significant value p for the calculation was set at 0.005.

**SVM Algorithm**

SVM or Support Vector Machine is a linear model for classification and regression problems. It can solve linear and non-linear problems and work well for many practical problems. The idea of SVM is simple: The algorithm creates a line or a hyperplane which separates the data into classes. In machine learning, the radial basis function kernel, or RBF kernel, is a popular kernel function used in various kernelized learning algorithms. In particular, it is commonly used in support vector machine classification. As a simple example, for a classification task with only two features (like the image above), you can think of a hyperplane as a line that linearly separates and classifies a set of data. Machine learning involves predicting and classifying data and to do so we employ various machine learning algorithms according to the dataset. Intuitively, the further from the hyperplane our data points lie, the more confident we are that they have been correctly classified. We therefore want our data points to be as far away from the hyperplane as possible, while still being on the correct side of it. So when new testing data is added, whatever side of the hyperplane it lands will decide the class that we assign to it.

## Pseudocode

**Inputs:** Determine the various face detection of driver drowsiness and test data, D=[X,Y]; X(array of input), Y(array of class labels)

**Outputs:** Determine the calculated accuracy. Select the optimal value of cost and gamma for SVM.

**Function:**

**while**(face detection is not met) do

Implement SVM for each data point.

Implement SVM classify for testing data points

**and while**

**Return** accuracy

**Random Forest Algorithm**

Random forests is an [ensemble learning](https://en.wikipedia.org/wiki/Ensemble_learning) method for [classification](https://en.wikipedia.org/wiki/Statistical_classification), [regression](https://en.wikipedia.org/wiki/Regression_analysis) and other tasks that operates by constructing a multitude of [decision trees](https://en.wikipedia.org/wiki/Decision_tree_learning) at training time. For classification tasks, the output of the random forest is the class selected by most trees. For regression tasks, the mean or average prediction of the individual trees is returned. Random decision forests correct for decision trees' habit of [overfitting](https://en.wikipedia.org/wiki/Overfitting) to their [training set](https://en.wikipedia.org/wiki/Test_set). Random forests generally outperform [decision trees](https://en.wikipedia.org/wiki/Decision_tree_learning), but their accuracy is lower than gradient boosted trees. However, data characteristics can affect their performance. Random Forest can help us to reduce or regularize the coefficients to their performance. Random Forest comes under L1 order technique as the key difference between the L1 and L2 are the drowsiness terms.

**Pseudocode**

**Input:** Predict and store the outcome of each randomly created decision rees on given test data and compute the total face images for individual class. Declare majority class as the final outcome class

**Output:** Final predicted class

**Function:**

* Randomly select “k” features from total “m” features.

Where k << m

* Among the “k” features, calculate the node “d” using the best split point.
* Split the node into daughter nodes using the best split.
* Repeat 1 to 3 steps until “l” number of nodes has been reached.
* Build forest by repeating steps 1 to 4 for “n” number times to create “n” number of trees.

The beginning of random forest algorithm starts with randomly selecting “k” features out of total “m” features. In the image, you can observe that we are randomly taking features and observations. In the next stage, we are using the randomly selected “k” features to find the root node by using the [best split](https://dataaspirant.com/2017/01/30/how-decision-tree-algorithm-works/) approach. In the next stage, we will be calculating the daughter nodes using the same best split approach. Will the first 3 stages until we form the tree with a root node and having the target as the leaf node. Finally, we repeat 1 to 4 stages to create “n” randomly created trees. These randomly created trees form the random forest.

**STATISTICAL ANALYSIS**

The output is created with Python. On a Windows 10 machine with an Intel Core i5-8250U processor running at 3.20GHz and 8GB of RAM, all of the tests for this study were run. The Novel SVM and Random Forest are statistically analyzed in this study using the SPSS programme. Using SPSS, we computed the means, standard deviations, and standard errors of means in order to compare the two samples independently. While SVM and Random forest are independent variables, accuracy is a dependent variable. The Independent samples T-Test analysis has been performed by analyzing the above collected data between the Novel SVM algorithm and Random Forest Algorithm.

**RESULTS**

The accuracy of the Novel SVM algorithm and the Random Forest Algorithm are contrasted in Figure 1. Compared to the Random forest classification model, which has an accuracy rating of 88.67%, the Novel SVM is more accurate. The SVM classifier and Random Forest classifier are very different from one another (test of independent samples, p 0.005). Along the X-axis, the accuracy rates for SVM and Random Forest are displayed. Y-axis: 95% confidence interval around the mean keyword identification accuracy, 1 standard deviation.

Table 1 shows the T-Test results of the proposed Novel SVM algorithm and the comparison Random Forest which has been run numerous times in the Jupyter notebook with a sample size of 10. From Table 1, it has been observed that the accuracy of the SVM algorithm is 97.70% and for the Random Forest algorithm the accuracy is found to be 91.20%. The standard deviation and the Standard Error Mean has also been calculated for the Novel SVM algorithm and for the Random Forest algorithm.

The statistical computations, including mean, standard deviation, and mean standard error, for the Random Forest and SVM classifiers are shown in Table 2. The t-test uses the accuracy level parameter. The Random Forest classification algorithm has a mean accuracy of 89.37 percent compared to the suggested method's mean accuracy of 88.52 percent. The Random forest algorithm's Standard Deviation is 4.63649, while SVM is 4.33037. The Random forest approach has a mean standard error of 1.27164 while the SVM method's is 1.49563.

In comparison to the Random Forest classifier, Table 3 shows the statistical computations for the independent variables of the SVM. The accuracy rate has a significance level of 0.670. The independent samples T-test is used to compare the SVM and Random Forest algorithms with a 95% confidence interval and a significance threshold of 0.554. This test of independent samples includes the following statistical significance indicators: significance two-tailed p =0.001(p < 0.005), a p value of 0.01, mean difference, standard error of mean difference, and lower and upper interval differences.

**DISCUSSION**

The proposed Novel SVM and Random Forest model's performance is simulated using Python in a windowed environment. The training set of the neural network comprises 70% of the entire database, whereas the test set comprises 30%. On the basis of performance analysis structure, the SVM approach is successfully compared against the Random Forest(D. F. Dunges and R. Grace 1998). The system is able to extract features and parameters from the data set and save them in a CSV file for subsequent processing of face images. An accuracy study has been conducted to determine the significance two-tailed p =0.001(p > 0.005) of each input parameter[(Silhavy 2019)](https://paperpile.com/c/gihtuk/zEye). The SVM algorithm produces more accurate results than the Random Forest algorithm. Experiment findings reveal that the proposed SVM strategy achieved 97.7 percent accuracy, compared to 91.20 percent accuracy for the Random Forest method.

The presentation upsides of the arrangement of ready and sleepiness state (ready versus marginally languid, ready versus reasonably tired or more) on account of utilizing full crossover measures are recorded in Table 3. Two group calculations (SVM, RF) accomplished higher upsides of all exhibitions contrasted with the DT calculation[(Syed-Abdul et al. 2020)](https://paperpile.com/c/gihtuk/Q0yK). The RF calculation accomplished particularly higher upsides of discovery exactness, accuracy, and F1 contrasted with the SVM calculation while grouping the ready and the marginally sluggish express, physiological conditions; its recognition precision was 97.77%[(Rani, Subhashree, and Devi 2016)](https://paperpile.com/c/gihtuk/fleD). The SVM calculation accomplished higher upsides of discovery exactness, accuracy, and F1 contrasted with the RF calculation while ordering the ready and the reasonably (or more than moderately) drowsy state; its detection accuracy was 91.20% which helps in reducing road traffic accidents.

The calculations' presentation values on account of barring physiological conditions and sleepiness are recorded in Table 4. The RF calculation accomplished higher upsides of discovery exactness, accuracy, review and F1 contrasted with the MVC calculation in all cases.[(Li, W.-C., Ou, W.-L., Fan, C.-P., Huang, C.-H., Shie, Y.-S 2016)](https://paperpile.com/c/gihtuk/gjiO) The RF calculation accomplished values of 78.7% and 88.67% detection accuracy in the case of classifying the alert vs. slightly drowsy, and the alert vs. moderately drowsy state, respectively. When physiological conditions were excluded, detection accuracy decreased by 3.5 %~9.0% compared to the case in which all measures were used.

**CONCLUSION**

The aim of the present experimentation research is to detect the face of driver drowsiness to reduce road traffic accidents. A non-invasive system to localize the eyes and monitor fatigue was developed. Information about the eyes position is obtained through self-developed image processing algorithm.When you run the code, it will open the webcam and will capture the video and gives output based on your eyelid closure. This drowsiness detection system helps the drivers a lot and prevents many road accidents that are caused due to drowsiness. The novel SVM and Random Forest are implemented in the suggested model in this study, where the SVM achieves higher levels of accuracy. The SVM is 97.7% more accurate than the Random Forest, whose accuracy rating is just 91.20% accurate, in an Enhanced Early Object Detection of Driver Drowsiness with enhanced accuracy.

# DECLARATIONS

## Conflict of Interests

No conflict of Interest in this manuscript.

## Authors Contributions

Author NJR was involved in data collection, data analysis and manuscript writing. Author SSA was involved in the conceptualization, data validation and critical review of manuscript.

## Acknowledgements

The authors would like to express their gratitude towards Saveetha School of Engineering, Saveetha Institute of Medical And Technical Sciences (Formerly known as Saveetha University) for providing the necessary infrastructure to carry out this work successfully.

## Funding

We thank the following organizations for providing financial support that enabled us to complete the study.

1. MindPlay Software Services Pvt. Ltd, Chennai
2. Saveetha School of Engineering
3. Saveetha Institute of Medical And Technical Sciences
4. Saveetha University

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**TABLES AND FIGURES**

**TABLE -1:** The performance measurements of the comparison between the SVM and Random Forest classifiers are presented in Table 1. The SVM classifier has an accuracy rate of 97.70, whereas the Random Forest classification algorithm has a rating of 91.20. With a greater rate of accuracy, the SVM classifier surpasses the Random Forest in drowsiness detection

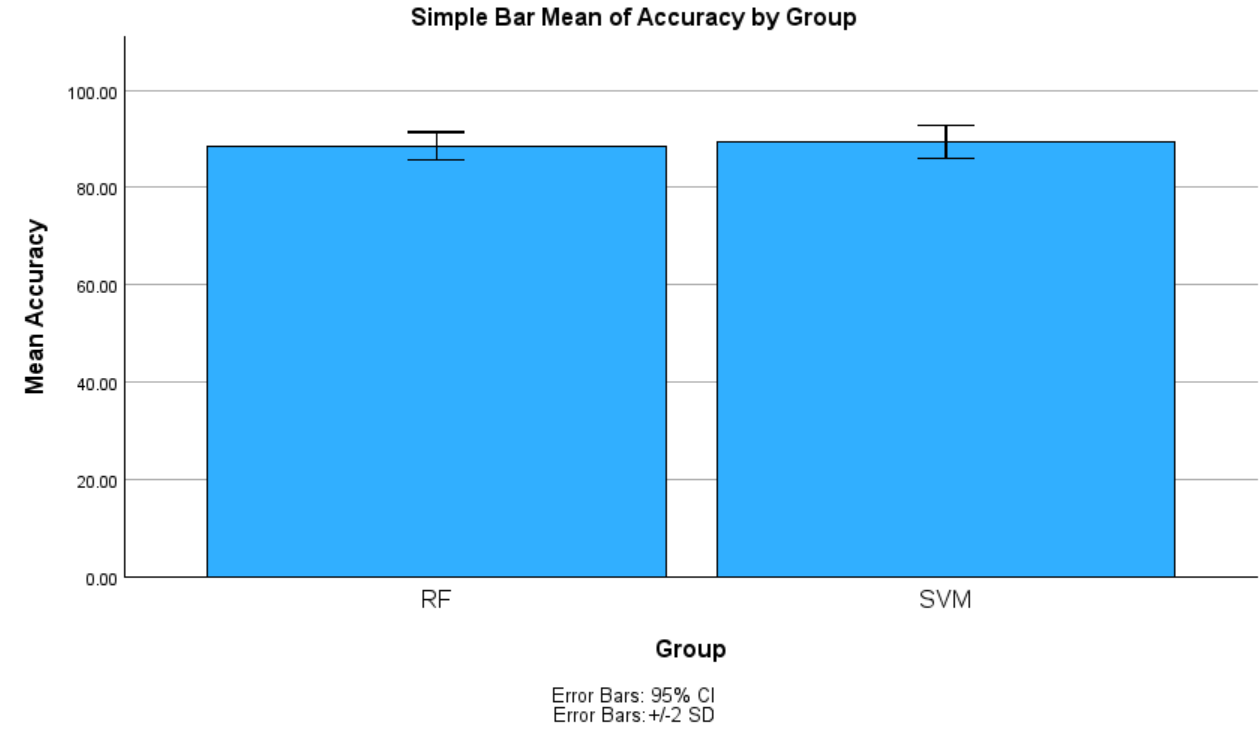
| S.0 | SVM | RANDOM FOREST |
| --- | --- | --- |
| 1 | 97.70 | 91.20 |
| 2 | 88.00 | 84.00 |
| 3 | 93.00 | 88.00 |
| 4 | 88.00 | 93.00 |
| 5 | 94.00 | 88.00 |
| 6 | 85.00 | 94.00 |
| 7 | 82.00 | 85.00 |
| 8 | 88.00 | 82.00 |
| 9 | 92.00 | 88.00 |
| 10 | 86.00 | 92.00 |

**Table-2 :** Presents the statistical analysis results of the Novel SVM algorithm and the Random Forest algorithm, comparing the mean accuracy, standard deviation, and standard error mean values across 10 sample datasets.

|  | **Algorithm** | **N** | **Mean** | **Std.**  **Deviation** | **Std. Error Mean** |
| --- | --- | --- | --- | --- | --- |
| **Accuracy** | Novel SVM  Random Forest | 10  10 | 89.3700  88.5200 | 4.33037  4.63649 | 1.49563  1.27164 |

**Table 3:** An independent sample T-Test was conducted to determine the significance of the difference between the two groups, using a significance level of p=0.670 (p>0.005), indicating that the difference is statistically significant.

|  | **Leven’s Test for Equality of**  **Variances** | | **T-Test for Equality of Means** | | | | | **95%**  **Confidence Interval of the Difference** | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **F** | **Sig.** | **t** | **df** | **Sig. (2-**  **tailed )** | **Mean Difference** | **Std. Error Difference** | **Lowe r** | **Upper** |
| **Accuracy** |  |  |  |  |  |  |  |  |  |
| Equal Variances assumed | .364 | .554 | .443 | 18 | .670 | .85000 | .1.96315 | -3.27443 | 4.97443 |
|  |  |  |  |  |  |  |  |  |  |
| Equal Variances not assumed |  |  | .433 | 17.546 | .670 | .85000 | 1.96315 | -3.28209 | 4.98209 |

****

**Fig. 1.** This figure shows the comparison between the SVM algorithm and the Random Forest algorithm in terms of Mean Accuracy. The Mean accuracy of the Novel SVM is better than the Mean accuracy of the SVM algorithm. X-axis: Novel SVM algorithm vs Random Forest algorithm, Y-axis: Mean Accuracy. Error Bar +/-1SD