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

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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), Novel 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 KNN. **Materials and Methods**: In this we have utilized two calculations, named SVM and KNN. During a time where headway of self-driving or computerized vehicles were expanding, for guaranteeing the security of travelers was more critical than before. This is many times exceptionally when the traveler or driver can't able to drive. The mean exactness of the current examination has been determined under directed learning with 0.8 as the alpha worth, a G-Power worth of 0.8, and CI of 95%. **Result**: Subsequent to carrying out this groundwork, the Novel SVM has accomplished an exactness of 97.70% and the KNN calculation has accomplished a precision of 92.77%. An Autonomous examples T-Test examination has been executed, and its importance esteem is viewed as p=.001 (p<0.005), proposing factual importance. **Conclusion:** In this current exploration, Novel SVM calculation is grouped with the KNN calculation. Subsequent to carrying out the ongoing groundwork analyze, the Novel SVM calculation has been found to have more flawlessness than the KNN.

**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**

Drowsiness detection works to prevent road traffic accidents created by microsleep, fatigue and lack of attention [(Picot et al. 2008)](https://paperpile.com/c/8Xwkp9/OqhX). Driver drowsiness detection systems generally come as one tool, one part of Advanced Driver Assistance Systems (ADAS). These are various programs and technologies designed to make driving safer and lessen the chances of human error resulting in catastrophic road traffic accidents [(Liu et al. 2010)](https://paperpile.com/c/8Xwkp9/NtfP). These can range from warning drivers if there’s something in their blind spot, to automatic emergency braking. To prevent road traffic accidents due to drowsy state driving, it is efficient for face detection of driver drowsiness early and accurately (B. Schlkopf-A. Blake, S. Romdhani, and P. Torr 2018). Once the system has established that the driver’s movements are erratic and they don’t seem alert, other factors may then be taken into account.  Hence, checking a driver's looks and physiological conditions is a broadly acknowledged strategy for recognizing driver sleepiness and helps for reducing road traffic accidents [(Borghini et al. 2014)](https://paperpile.com/c/8Xwkp9/8XL2). In the proposed system, which is applied on videos obtained from a public drowsiness detection dataset, the face region is first localized in each frame. Then, the eye region is detected and extracted as the region of interest using facial landmarks detector. Following that, the eye aspect ratio value of each frame is calculated, analyzed, and recorded. Finally, three different classifiers, namely, linear support vector machine, random forest, and sequential neural network, are employed to improve the detection accuracy. Subsequently, the extracted data are classified to determine if the driver's eyes are closed or open. An alarm will then be triggered to alert the drowsy driver if an eye closure is recognized for a specified duration of time.

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. This technology is still in the early research stage of development (Y. Yin, Y. Xio 2010). Based on the work completed thus far, following modifications can be implemented - Capture individual drivers steering activity while drowsy [(Seifoory et al. 2011)](https://paperpile.com/c/8Xwkp9/Tc2C). Conduct additional simulator experiments to validate the algorithm, test additional road. conditions, and test a more diversified group of drivers, Test and refine the algorithm based on the road test data, and conduct research on warning systems integrated with the detection system has likewise been utilized to recognize driver sluggishness or sleepiness [(Danisman et al. 2010)](https://paperpile.com/c/8Xwkp9/mirv). What's more, physiological conditions are broadly used to identify driver sleepiness since it straightforwardly mirrors the inward physiological conditions of drivers in term to reduce road traffic accidents. This work compares used KNN algorithm for early object detection of driver drowsiness [(Jap et al. 2009)](https://paperpile.com/c/8Xwkp9/ZmUW) The Novel SVM is likewise generally utilized for grouping as an administered learning strategy [(Bhattacharyya et al. 2018)](https://paperpile.com/c/8Xwkp9/LFAX). 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 to reduce road traffic accidents[(Welsh et al. 2002)](https://paperpile.com/c/8Xwkp9/PYoL).

The KNN algorithm was used to divide the drivers’ level of drowsiness into three stages as in grouped according to the time of eye remaining closed or the blinking rate, and according to each group differential alarms go off for each stages [(Kim and Shin 2014)](https://paperpile.com/c/8Xwkp9/u2XG). Besides, it computes the significance of elements. The consequences of the past review showed that the KNN calculation can acquire roughly 80% precision while characterizing the alarm and somewhat sleepiness states[(McKnight 1998)](https://paperpile.com/c/8Xwkp9/1k42). Drowsiness detection systems monitor the driver condition and generate an alarm if drowsiness signs are detected. In this paper, a real-time visual-based driver drowsiness detection system is presented aiming to detect drowsiness by extracting an eye feature called the eye aspect ratio[(Dinges and Grace 1998)](https://paperpile.com/c/8Xwkp9/gACH). There are many methods to detect drowsiness that exist to keep a check on the drivers’ state and make them awake by ringing alarms, if they are not concentrated enough on driving. In this drowsiness detection system, the system detects and measures the drivers’ drowsiness status, such as blinking, i.e., duration of closing of eyes which is Eye Aspect Ratio (EAR), using images from the video and this program makes warning alarms go off for each level of drowsiness when it detects drowsiness in driving [(Chowdhury et al. 2018)](https://paperpile.com/c/8Xwkp9/aICS). Another purpose of this work is to gain insights about certain behavioral characteristic to enable further development of robust and reliable driver state classification systems. Forth is purpose, the k-Nearest Neighbor(k-NN) algorithm is used to classify the driver’s state of drowsiness based on the eye closure and head movement characteristics.

**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. 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 KNN 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**

Support Vector Machine or SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning. The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane. SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine.SVM algorithm finds the closest point of the lines from both the classes. These points are called support vectors. The distance between the vectors and the hyperplane is called as margin. And the goal of SVM is to maximize this margin. The hyperplane with maximum margin is called the optimal hyperplane.

## 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

**KNN Algorithm**

K-Nearest Neighbours is one of the most basic yet essential classification algorithms in Machine Learning. It belongs to the supervised learning domain and finds intense application in pattern recognition, data mining and intrusion detection. It is widely disposable in real-life scenarios since it is non-parametric, meaning, it does not make any underlying assumptions about the distribution of data (as opposed to other algorithms such as [GMM](https://en.wikipedia.org/wiki/Mixture_model), which assume a Gaussian distribution of the given data).We are given some prior data (also called training data), which classifies coordinates into groups identified by an attribute.[(I. Garcia, S. Bronie 2010)](https://paperpile.com/c/kC6PzF/OFbt).

**Pseudocode**

**Input:** Training dataset T,

I=(i1,i2,i3,...,in) // value of the predictor variable in testing dataset

**Output:** A class of testing data of face detection images

**Function:**

* Load the training data.
* Prepare data by scaling, missing value treatment, and dimensionality reduction as required.
* Find the optimal value for K:
* Predict a class value for new data:
  + Calculate distance(X, Xi) from i=1,2,3,….,n.  
    where X= new data point, Xi= training data, distance as per your chosen distance metric.
  + Sort these distances in increasing order with corresponding train data.
  + From this sorted list, select the top ‘K’ rows.
  + Find the most frequent class from these chosen ‘K’ rows. This will be your predicted class.

K can be kept as an odd number so that we can calculate a clear majority in the case where only two groups are possible (e.g. Red/Blue). With increasing K, we get smoother, more defined boundaries across different classifications. Also, the accuracy of the above classifier increases as we increase the number of data points in the training set. Euclidean distance is the most popular distance metric. You can also use Hamming distance, Manhattan distance, Minkowski distance as per your need. For predicting class/ continuous value for a new data point, it considers all the data points in the training dataset. Finds new data point’s ‘K’ Nearest Neighbors (Data points) from feature space and their class labels or continuous values.

**STATISTICAL ANALYSIS**

The result is made with Python. On a Windows 10 machine with an Intel Center i5-8250U processor running at 3.20GHz and 8GB of Smash, the tests for this review were all run. The Clever SVM and KNN are measurably dissected in this study utilizing the SPSS program. Utilizing SPSS, we registered the means, standard deviations, and standard blunders of means to freely look at the two examples. While SVM and KNN are free factors, precision is a reliant variable. The Autonomous examples T-Test investigation has been performed by breaking down the above gathered information between the Novel SVM calculation and KNN Calculation.

**RESULTS**

Figure 1 compares the accuracy of the Novel SVM algorithm with the KNN Algorithm. The Novel SVM is more accurate than the KNN classification model, which has an accuracy score of 97.70. A test of independent samples revealed a significant difference between the KNN and SVM classifiers (p 0.005). The accuracy rates for SVM and KNN are shown along the X-axis. Y-axis: 95% confidence interval around the mean of the standard deviation for keyword identification accuracy.

The suggested Novel SVM algorithm's T-Test results are shown in Table 1, along with those of the comparative KNN, with a sample size of 10 runs in the Jupyter notebook. According to Table 1, the SVM algorithm's accuracy is 97.70%, while the kNN algorithm's accuracy is determined to be 92.77%. The Novel SVM method and the KNN algorithm have also had their standard deviation and standard error mean assessed.

Table 2 displays the statistical calculations for the KNN and SVM classifiers, including mean, standard deviation, and mean standard error. The accuracy level parameter is used in the t-test. The proposed method's mean accuracy is 97.70 percent, whereas the KNN classification algorithm's mean accuracy is 92.77 percent. The standard deviation of the KNN method is 2.50600, whereas that of the SVM is 2.44683. The SVM method's mean standard error is 0.77376 whereas the KNN approach is 0.79247.

Table 3 displays the statistical calculations for the independent variables of the SVM in comparison to the KNN classifier. The significance threshold for the accuracy rate is 0.857. The SVM and KNN algorithms are compared using the independent samples T-test, with a 95% confidence interval and a significance level of 0.033. The statistical significance indicators used in this test of independent samples are the mean difference, standard error of the mean difference, lower and upper interval differences, significance two-tailed p = 0.001(p < 0.005), and a p value of 0.001.

**DISCUSSION**

Python is used to simulate the performance of the proposed Novel SVM and KNN model in a windowed setting. The neural network's test set makes up 30% of the total database, while the training set makes up 70%. The SVM machine learning technique is effectively evaluated against the KNN on the basis of performance analysis structure (D. F. Dunges and R. Grace 1998). In order to process face photographs later, the system may extract features and parameters from the data set and save them in a CSV file. To ascertain the importance of two-tailed p =0.001(p > 0.005) of each input parameter, an accuracy study was undertaken. Compared to the KNN method, the SVM algorithm yields more accurate results. The results of the experiment show that the suggested SVM technique obtained 97.70% accuracy, compared to KNN

Table 3 lists the benefits of the ready vs somewhat drowsy and ready versus fairly fatigued or more arrangements of readiness and sleepiness condition as a result of using complete crossover assessments. In comparison to the DT calculation, two machine learning group computations (SVM, KNN) had larger upsides across the board[(Rani et al. 2016)](https://paperpile.com/c/8Xwkp9/L6Cl). When grouping the ready and the slightly slow express, physiological conditions, the KNN calculation achieved especially larger upsides of discovery exactness, accuracy, and F1 compared to the SVM calculation; its recognition precision was 97.70%. While ordering the ready and the reasonably (or more than moderately) tired condition, the SVM calculation achieved greater upsides of discovery exactness, accuracy, and F1 compared with the KNN calculation; its detection accuracy was 92.77%.

Table 4 lists the presenting values of the computations after accounting for physiological conditions and tiredness. In every instance, the KNN computation outperformed the MVC calculation in terms of discovery exactness, correctness, review, and F1 [(Li et al. 2016)](https://paperpile.com/c/8Xwkp9/v9Un) When identifying the alert vs. slightly drowsy and alert vs. moderately drowsy states, the KNN computation achieved values of 88.7% and 92.77% detection accuracy, respectively. Compared to the scenario when all measurements were employed, detection accuracy fell when physiological conditions were removed by 3.5% to 9.0%.

**CONCLUSION**

The aim of this project is to develop a drowsiness detection system. The focus is on designing a system that will accurately monitor the open or closed state or sleepiness of the drivers eyes in real-time. By monitoring the eyes, it is believed that the symptoms of driver fatigue can be detected early enough to avoid a car accident. Detection of drowsy involves a pattern of images of a face, and the observation of eye movements and sleepiness, blink rate. The analysis of face images is a popular research area with applications such as face recognition, virtual tools, and human identification security systems. The novel SVM and KNN are implemented in the suggested model in this study, where the SVM achieves higher levels of accuracy. The SVM is 97.70% more accurate than the KNN, whose accuracy rating is 92.77% accurate, in an Enhanced Early object Detection of Driver Drowsiness with enhanced accuracy using machine learning approach.

# 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.

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**TABLES AND FIGURES**

**TABLE -1:** The performance measurements of the comparison between the SVM and KNN classifiers are presented in Table 1. The SVM classifier has an accuracy rate of 97.70, whereas the KNN classification algorithm has a rating of 92.77. With a greater rate of accuracy, the SVM classifier surpasses the KNN in drowsiness detection.

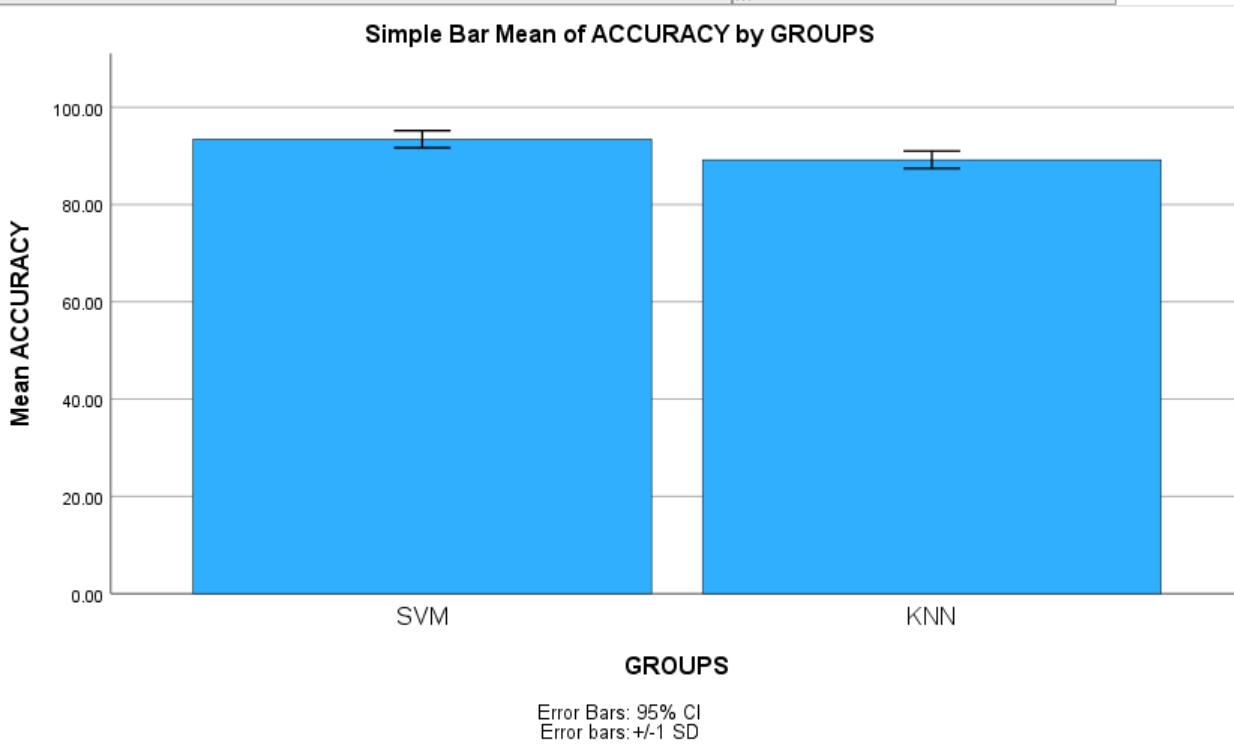
| S.0 | SVM | KNN |
| --- | --- | --- |
| 1 | 97.70 | 92.77 |
| 2 | 96.40 | 92.00 |
| 3 | 95.33 | 91.22 |
| 4 | 94.33 | 90.80 |
| 5 | 93.22 | 89.80 |
| 6 | 92.40 | 88.56 |
| 7 | 92.00 | 88.00 |
| 8 | 91.86 | 87.60 |
| 9 | 91.00 | 86.00 |
| 10 | 90.13 | 85.42 |

**Table-2 :** Presents the statistical analysis results of the Novel SVM algorithm and the KNN 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  KNN | 10  10 | 93.4370  89.2170 | 2.44683  2.50600 | .77376  .79247 |

**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=0.001 (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 p value)** | **Mean Differ ence** | **Std. Error Differe nce** | **Lowe r** | **Upper** |
| **Accuracy** |  |  |  |  |  |  |  |  |  |
| Equal Variances assumed | .033 | .857 | 3.810 | 18 | .001 | 4.22000 | 1.10757 | 1.89309 | 6.54691 |
|  |  |  |  |  |  |  |  |  |  |
| Equal Variances not assumed |  |  | 3.810 | 17.990 | .001 | 4.22000 | 1.10757 | 1.89299 | 6.54701 |

**Fig. 1.** This figure shows the comparison between the SVM algorithm and the KNN 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 KNN algorithm, Y-axis: Mean Accuracy. Error Bar +/-1SD