## Title Page

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

Nagireddy Jashwanth Reddy¹, S.S. Arumugam2

Nagireddy Jashwanth Reddy¹,

Research Scholar,

Department of Computer Science And Engineering,

Saveetha School Of Engineering,

Saveetha Institute Of Medical and Technical Sciences,

Saveetha University , Chennai , Tamil Nadu , Pincode : 602105.

[jaswanthkumarreddy18@saveetha.com](mailto:jaswanthkumarreddy18@saveetha.com%20)

S.S. Arumugam2

Project Guide, Corresponding Author,

Department Of Information Security,

Saveetha School Of Engineering,

Saveetha Institute Of Medical and Technical Sciences,

Saveetha University , Chennai , Tamil Nadu , Pincode : 602105.

[arumugamss.sse@saveetha.com](mailto:arrmugamss.sse@saveetha.com)

**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 goal is to improve early object identification of driver drowsiness using machine learning by contrasting SVM with Naive Bayes in supervised learning approaches. **Materials and Methods**: SVM and Naive Bayes are two algorithms that we have used in this project. The development of technologies for detecting and avoiding drowsiness at the wheel is a major challenge in the field of accident avoidance systems. Because of the hazard that drowsiness presents on the road, methods need to be developed for counteracting its effects**.** The mean accuracy of the current study was computed using supervised learning with an alpha value of 0.8, a G-Power value of 0.8, and a 95% confidence interval. **Result**: the Novel SVM and Naive Bayes algorithms both reached accuracy levels of 97.70% and 93.50%, respectively. Following the execution of an Independent Samples T-Test analysis, the significance value was determined to be p=<.001 (p<0.005), indicating statistical significance. **Conclusion:** The Naive Bayes method and the Novel SVM algorithm are combined in the current study. The Naive Bayes method has been discovered to have greater perfection than the Novel SVM algorithm after carrying out the present study experiment.

**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 system for drivers, which alerts the driver if they fall asleep due to fatigue while still driving and to reduce the road traffic accidents. Many people face long nights at work. Truck drivers, security guards, healthcare professionals. Jobs that are fundamental to society and to the health, wellbeing and comfort of the general population. As a result, getting behind the wheel while feeling tired is not uncommon. It’s something most drivers have probably done. It can be incredibly dangerous, unless we find a way to warn drivers when their tiredness has become too severe and is impairing their driving which may lead to 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 (B. Schlkopf-A. Blake, S.Romdhani, and P. Torr 2018). Also we have proposed new detection methods using machine learning techniques. To estimate the drivers' state we use facial regions corresponding to the entire face [(Picot et al. 2008)](https://paperpile.com/c/8Xwkp9/OqhX). There is a solid relationship between genuine tiredness and emotional assessment in view of looks [(Liu et al. 2010)](https://paperpile.com/c/8Xwkp9/NtfP). Driver drowsiness and attention warning and advanced driver distraction warning systems shall be designed in such a way that those systems do not continuously record nor retain any data other than what is necessary in relation to the purposes for which they were collected or otherwise processed within the closed-loop system. Furthermore, those data shall not be accessible or made available to [third parties](https://en.wiktionary.org/wiki/third_party) at any time and shall be immediately deleted after processing. Those systems shall also be designed to avoid overlap and shall not prompt the driver separately and concurrently or in a confusing manner, physiological conditions where one action triggers both systems. Hence, checking a driver's looks is a broadly acknowledged strategy for recognizing driver sleepiness and reduces road traffic accidents [(Borghini et al. 2014](https://paperpile.com/c/8Xwkp9/8XL2)).

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. Driver drowsiness detection systems can use cameras[(Welsh et al. 2002)](https://paperpile.com/c/8Xwkp9/PYoL), eye tracking sensors and other hardware to monitor visual cues, where drowsiness can be detected through yawning frequency, eye-blinking frequency, eye-gaze movement, head movement and facial expression’s (Y. Yin, Y. Xio 2010). The systems can also monitor driving input behavior to notice when there are erratic steering movements, pedal use and lane deviations which helps in reducing road traffic accidents [(Seifoory et al. 2011)](https://paperpile.com/c/8Xwkp9/Tc2C). What's more, physiological conditions are broadly used to identify driver sleepiness since it straightforwardly mirrors the inward physiological conditions of drivers and to reduce road traffic accidents [(Danisman et al. 2010)](https://paperpile.com/c/8Xwkp9/mirv). Different car models have different systems, but in most cases the driver will be alerted to their potential drift of attention with some sort of noise, or vibration of the steering wheel or seat[(Bhattacharyya et al. 2018)](https://paperpile.com/c/8Xwkp9/LFAX). The system may also remind the driver to take a break, especially if they have been on the road for an extended period of time which helps in reducing road traffic accidents [(Jap et al. 2009)](https://paperpile.com/c/8Xwkp9/ZmUW).

The Naïve Bayes Classifier is one of the simple and most effective Classification algorithms which helps in building the fast machine learning models that can make quick predictions[(McKnight 1998)](https://paperpile.com/c/8Xwkp9/1k42). It is a probabilistic classifier, which means it predicts on the basis of the probability of an object [(Kim and Shin 2014)](https://paperpile.com/c/8Xwkp9/u2XG). Besides, it computes the significance of elements. The results of the past review showed that the Naive Bayes calculation can acquire roughly 80% precision while characterizing the alarm and somewhat sleepiness states[(Welsh et al. 2002)](https://paperpile.com/c/8Xwkp9/PYoL). To overcome this difﬁculty and make calculations increasingly tractable, we use the well-known "naïve Bayes independence assumption," which states that the probabilities of each attribute are conditionally independent of each other [(Chowdhury et al. 2018)](https://paperpile.com/c/8Xwkp9/aICS).To extract facial landmarks of drivers, Dlib library was imported and deployed. The library utilizes a prepared face detector, which depends on an alteration to the histogram of situated inclinations and uses linear SVM (support vector machine) technique for object recognition. Face landmark were initialized and captured which were used for calculating distance between the points [(Dinges and Grace 1998)](https://paperpile.com/c/8Xwkp9/gACH). EAR stand for Ear Aspect Ratio where numerator denotes height of eye and denominator denotes the width of eye, the numerator calculates the distance between the upper eyelid and the lower eyelid[(Victor, Lee, and Regan 2013)](https://paperpile.com/c/gihtuk/x2xg). The denominator represents the horizontal distance of the eye. When the eyes are open, the numerator value increases, thus increasing the EAR value, and when the eyes are closed the numerator value decreases, thus decreasing the EAR value.

**MATERIALS AND METHODS**

The Simats Institute of Medical and Technical Sciences (SIMATS), Chennai, houses the Saveetha School of Engineering's Machine Learning Laboratory, where the current experimentation work has been carried out. This particular research project made use of the driver drowsiness dataset. The database is set up so that only 25% of the available capacity is used for testing, and the other 75% is reserved for training. There are two sets of ten data samples each, for a total of twenty samples. The Novel SVM approach was used in Group I, and the Naive Bayes algorithm was used in Group 2. The implementation makes use of Python-coded software. For the calculation, the G power was set at 80%, the confidence interval at 95%, and the significant value at p was set at 0.005.

**SVM Algorithm**

SVM or Support Vector Machine is a linear regression model for problems involving classification and regression. It works well for a range of real-world issues and can solve both linear and non-linear problems. The SVM's basic premise is as follows: A line or a hyperplane that categorises the data is produced by the algorithm. The radial basis function kernel, or RBF kernel, is a well-known kernel function in machine learning that is utilised in various kernelized learning techniques. It is frequently employed, particularly in support vector machine classification. A hyperplane is a line that linearly separates and categorises a set of data (like in the above graphic) for a classification problem with only two features. Machine Learning includes anticipating and grouping information and to do so we utilize different AI calculations as indicated by the dataset. Instinctively, the further from the hyperplane our information focuses lie, the more certain we are that they have been accurately grouped. We in this way need our information to be as distant from the hyperplane as could be expected, while as yet being on the right half of it. So while new testing information is added, whatever side of the hyperplane it terrains will conclude the class that we dole out 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

**Naive Bayes Algorithm**

The Naïve Bayes classifier is a directed AI calculation, which is utilized for grouping undertakings, similar to message order. It is likewise important for a group of generative learning calculations, implying that it tries to demonstrate the conveyance of contributions of a given class or class. Dissimilar to discriminative classifiers, as strategic relapse, it doesn't realize which highlights are generally critical to separate between classes. Naïve Bayes is otherwise called a probabilistic classifier since it depends on Bayes' Hypothesis. It would be challenging to make sense of this calculation without making sense of the rudiments of Bayesian measurements. This hypothesis, otherwise called Bayes' Standard, permits us to "reverse" restrictive probabilities. Naive Bayes can assist us with lessening or regularize the coefficients to their presentation.[(I. Garcia, S. Bronie 2010)](https://paperpile.com/c/kC6PzF/OFbt).

**Pseudocode**

**Input:** Training dataset T,

F=(f1,f2,f3,...,fn) // value of the predictor variable in testing dataset

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

**Function:**

* Read the dataset of T
* Calculate the mean and standard deviation of predictor variables in each class.
* Repeat

calculate the probability of fi using the guass density equation in each class;

until the probability of each predictor variables in each class;

* Calculate the likelihood of each class;
* Get the greatest likelihood;

The class probabilities are simply the frequency of instances that belong to each class divided by the total number of instances. For example in a binary classification the probability of an instance belonging to class 1 would be calculated as: P(class=1) = count(class=1) / (count(class=0) + count(class=1)). In the simplest case each class would have the probability of 0.5 or 50% for a binary classification problem with the same number of instances in each class.

**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 Naive Bayes 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 Naive Bayes 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 Naive Bayes Algorithm.

**RESULTS**

The precision of the Novel SVM calculation and the Naive Bayes Calculation are differentiated in Figure 1. Contrasted with the Naive Bayes arrangement model, which has a precision rating of 93.5, the Novel SVM is more exact. The SVM classifier and Naive Bayes classifier are altogether different from each other (trial of free examples, p 0.005). Along the X-pivot, the precision rates for SVM and Naive Bayes are shown. Y-hub: 95% certainty span around the mean watchword recognizable proof precision, 1 standard deviation.

Table 1 shows the T-Test consequences of the proposed Novel SVM calculation and the correlation Naive Bayes which has been run various times in the Jupyter note pad with an example size of 10. From Table 1, it has been seen that the precision of the SVM calculation is 97.70% and for the Naive Bayes the exactness is viewed as 93.5%. The standard deviation and the Standard Mistake Mean has likewise been determined for the Original SVM calculation and for the Naive Bayes calculation.

The measurable calculations, including mean, standard deviation, and mean standard mistake, for the Naive Bayes and SVM classifiers are displayed in Table 2. The t-test utilizes the exactness level boundary. The Naive Bayes characterization calculation has a mean precision of 91.4920 percent contrasted with the recommended technique's mean exactness of 95.4990 percent. The Naive Bayes calculation's Standard Deviation is 1.44443, while SVM is 1.53388. The Naive Bayes approach has a mean standard error of 0.45673 while the SVM strategy's is 0.48506.

In contrast with the Naive Bayes classifier, Table 3 shows the factual calculations for the autonomous factors of the SVM. The exactness rate has an importance level of 0.029. The free examples T-test is utilized to look at the SVM and Naive Bayes calculations with a 95% certainty span and an importance limit of 0.79117. This trial of free examples incorporates the accompanying factual importance markers: importance two-followed p =0.001(p < 0.005), p is of 0.001, mean contrast, standard blunder of mean distinction, and lower and upper span contrasts.

**DISCUSSION**

The proposed Novel SVM and Naive Bayes model's exhibition is recreated involving Python in a windowed climate. The preparation set of the brain network includes 70% of the whole data set, while the test set contains 30%. Based on execution examination structure, the SVM approach is effectively analyzed against the Naive Bayes[(Silhavy 2019)](https://paperpile.com/c/gihtuk/zEye). The framework can extricate elements and boundaries from the informational collection and save them in a CSV document for resulting handling of face pictures. An exactness concentrate on has been directed to decide the importance two-followed p =0.001(p > 0.005) of each information boundary. The SVM calculation creates more exact outcomes than the Naive Bayes calculation. Try discoveries uncover that the proposed SVM technique accomplished 97.70 percent exactness, contrasted with 93.5 percent precision for the Naive Bayes strategy.

The potential gains of the plan of prepared and lethargy state (prepared versus hardly lazy, prepared versus sensibly drained or more) because of using full hybrid measures are kept in Table 3. Two gathering computations (SVM, Naive Bayes) achieved higher potential gains of all presentations that stood out from the DT estimation. The Naive Bayes estimation achieved especially higher potential gains of revelation precision, exactness, and F1 stood out from the SVM computation while gathering the prepared and the hardly slow express, physiological conditions; its acknowledgment accuracy was 97.70%[(Rani, Subhashree, and Devi 2016)](https://paperpile.com/c/gihtuk/fleD). The SVM estimation achieved higher potential gains of revelation precision, exactness, and F1 appeared differently in relation to the Naive Bayes computation while requesting the prepared and the sensibly (or more than decently) tired express; its identification precision was 93.5%.

The computations' show values because of accepting physiological conditions and sleepiness are kept in Table 4. The Naive Bayes computation achieved higher potential gains of disclosure precision, exactness, survey and F1 stood out from the MVC estimation 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 Naive Bayes computation achieved upsides of 89.8 and 92.30% discovery precision on account of ordering the ready versus marginally sluggish, and the ready versus decently sleepiness state, individually. At the point when physiological conditions were barred, location precision diminished by 3.5 %~9.0% contrasted with the case where all actions were utilized.

**CONCLUSION**

The aim of the present experimentation research is to detect the face of driver drowsiness. During the monitoring, the system is able to decide if the eyes are opened or closed. When the eyes have been closed and looks like sleepiness, a warning signal of voice command is issued.A drowsiness detection system developed around the principle of image processing judges the drivers alertness level on the basis of continuous eye closures. In addition, during monitoring, the system is able to automatically detect any eye localizing error and sleepiness that might have occurred. The novel SVM and Naive Bayes are implemented in the suggested model in this study, where the Naïve Bayes achieves higher levels of accuracy. The Naïve Bayes is 93.50% less accurate than the SVM, whose accuracy rating is just 97.70% 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.

## 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

**REFERENCES**

[Bhattacharyya, Siddhartha, Nabendu Chaki, Debanjan Konar, Udit Kr Chakraborty, and Chingtham Tejbanta Singh. 2018. *Advanced Computational and Communication Paradigms: Proceedings of International Conference on ICACCP 2017, Volume 2*. Springer.](http://paperpile.com/b/gihtuk/PZJL)

[Borghini, Gianluca, Laura Astolfi, Giovanni Vecchiato, Donatella Mattia, and Fabio Babiloni. 2014. “Measuring Neurophysiological Signals in Aircraft Pilots and Car Drivers for the Assessment of Mental Workload, Fatigue and Drowsiness.” *Neuroscience and Biobehavioral Reviews* 44 (July): 58–75.](http://paperpile.com/b/gihtuk/1Rid)

B. Schlkopf-A. Blake, S.Romdhani, and P. Torr, and A. Abdul Rahmat, "*MIROS crash*

*investigation and reconstruction: annual statistical 20015-2016,*" 2018.

[Chowdhury, Muhammad E. H., Samir Hussein El Beheri, Mohammed Nabil Albardawil, Ahmed Khaled Mohamed Moustafa, Osama Halabi, and Mustafa Serkan Kiranyaz. 2018. “Driver Drowsiness Detection Study Using Heart Rate Variability Analysis in Virtual Reality Environment.” In *Qatar Foundation Annual Research Conference Proceedings Volume 2018 Issue 3*, 2018:ICTPD1132. Hamad bin Khalifa University Press (HBKU Press).](http://paperpile.com/b/gihtuk/jjFK)

[Danisman, Taner, Ian Marius Bilasco, Chabane Djeraba, and Nacim Ihaddadene. 2010. “Drowsy Driver Detection System Using Eye Blink Patterns.” In *2010 International Conference on Machine and Web Intelligence*, 230–33.](http://paperpile.com/b/gihtuk/cpos)

[De, Sourav, Siddhartha Bhattacharyya, and Paramartha Dutta. 2018. *Intelligent Multidimensional Data and Image Processing*. IGI Global.](http://paperpile.com/b/gihtuk/NJFF)

[Dinges, D. F., and R. Grace. n.d. “PERCLOS: A Valid Psychophysiological Measure of Alertness as Assessed by Psychomotor Vigilance.” *US Department of Transportation, Federal Highway*.](http://paperpile.com/b/gihtuk/9uGK)

[Foster, Ian, Rayid Ghani, Ron S. Jarmin, Frauke Kreuter, and Julia Lane. 2020. *Big Data and Social Science: Data Science Methods and Tools for Research and Practice*. CRC Press.](http://paperpile.com/b/gihtuk/ltIe)

I . Garcia, S. Bronte, L. Bergasa, N. Hernandez, B. Delgado, and M. Sevillano, "*Vision-*

*based drowsiness detection for a realistic driving simulator,*" in Intelligent

TransportationSystems (ITSC), 2010 13th International IEEE Conference on, 2010,

pp. 887-894.

[Jap, Budi Thomas, Sara Lal, Peter Fischer, and Evangelos Bekiaris. 2009. “Using EEG Spectral Components to Assess Algorithms for Detecting Fatigue.” *Expert Systems with Applications* 36 (2, Part 1): 2352–59.](http://paperpile.com/b/gihtuk/Eli3)

[Kim, Jaeseok, and Hyunchul Shin. 2014. *Algorithm & SoC Design for Automotive Vision Systems: For Smart Safe Driving System*. Springer.](http://paperpile.com/b/gihtuk/k6Ft)

[Liu, Danghui, Peng Sun, Yanqing Xiao, and Yunxia Yin. 2010. “Drowsiness Detection Based on Eyelid Movement.” In *2010 Second International Workshop on Education Technology and Computer Science*, 2:49–52.](http://paperpile.com/b/gihtuk/Iuz1)

[Li, W.-C., Ou, W.-L., Fan, C.-P., Huang, C.-H., Shie, Y.-S. 2016. “Near-Infrared-Ray and Side-View Video Based Drowsy Driver Detection System: Whether or Not Wearing Glasses.” *IEEE*. https://doi.org/](http://paperpile.com/b/gihtuk/gjiO)[10.1109/APCCAS.2016.7803994](http://dx.doi.org/10.1109/APCCAS.2016.7803994)[.](http://paperpile.com/b/gihtuk/gjiO)

[McKnight, Douglas J. 1998. Method and apparatus for displaying grey-scale or color images from binary images. USPTO 5767828. *US Patent*, filed July 20, 1995, and issued June 16, 1998.](http://paperpile.com/b/gihtuk/5JPk) <https://patentimages.storage.googleapis.com/03/84/40/8dcfa762566c38/US5767828.pdf>[.](http://paperpile.com/b/gihtuk/5JPk)

[Picot, Antoine, Sylvie Charbonnier, and Alice Caplier. 2008. “On-Line Automatic Detection of Driver Drowsiness Using a Single Electroencephalographic Channel.” *Conference Proceedings: ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference* 2008: 3864–67.](http://paperpile.com/b/gihtuk/Hvi0)

[Rani, P. Sheela, P. Subhashree, and N. Sankari Devi. 2016. “Computer Vision Based Gaze Tracking for Accident Prevention.” In *2016 World Conference on Futuristic Trends in Research and Innovation for Social Welfare (Startup Conclave)*. IEEE. https://doi.org/](http://paperpile.com/b/gihtuk/fleD)[10.1109/startup.2016.7583976](http://dx.doi.org/10.1109/startup.2016.7583976)[.](http://paperpile.com/b/gihtuk/fleD)

[Seifoory, Hossein, Davood Taherkhani, Behnam Arzhang, Zahra Eftekhari, and Hamid Memari. 2011. “An Accurate Morphological Drowsy Detection.” *IEEE*.](http://paperpile.com/b/gihtuk/ofRW) <https://www.researchgate.net/profile/Behnam-Arzhang/publication/268062538_An_Accurate_Morphological_Drowsy_Detection/links/5481fbb60cf2f5dd63a81131/An-Accurate-Morphological-Drowsy-Detection.pdf>[.](http://paperpile.com/b/gihtuk/ofRW)

Sheela Rani, P., Subhashree, P., Sankari Devi, N.: *Computer vision based gaze tracking for*

*accident prevention (2016)*

[Silhavy, Radek. 2019. *Software Engineering Methods in Intelligent Algorithms: Proceedings of 8th Computer Science On-Line Conference 2019, Vol. 1*. Springer.](http://paperpile.com/b/gihtuk/zEye)

[Suthaharan, Shan. 2015. *Machine Learning Models and Algorithms for Big Data Classification: Thinking with Examples for Effective Learning*. Springer.](http://paperpile.com/b/gihtuk/UkBL)

[Syed-Abdul, Shabbir, Luis Fernandez Luque, Pei-Yun Sabrina Hsueh, Juan M. García-Gomez, and Begoña Garcia-Zapirain. 2020. *Data Analytics and Applications of the Wearable Sensors in Healthcare*. MDPI.](http://paperpile.com/b/gihtuk/Q0yK)

[Victor, Mr Trent W., John D. Lee, and Michael A. Regan. 2013. *Driver Distraction and Inattention: Advances in Research and Countermeasures, Volume 1*. Ashgate Publishing, Ltd.](http://paperpile.com/b/gihtuk/x2xg)

[Welsh, Tomihisa, Michael Ashikhmin, and Klaus Mueller. 2002. “Transferring Color to Greyscale Images.” In *Proceedings of the 29th Annual Conference on Computer Graphics and Interactive Techniques*, 277–80. SIGGRAPH ’02. New York, NY, USA: Association for Computing Machinery.](http://paperpile.com/b/gihtuk/7VRe)

**TABLES AND FIGURES**

**TABLE -1:** The performance measurements of the comparison between the SVM and Naive Bayes classifiers are presented in Table 1. The SVM classifier has an accuracy rate of 97.70, whereas the Naive Bayes classification algorithm has a rating of 93.50. With a greater rate of accuracy, the SVM classifier surpasses the Naive Bayes in drowsiness detection.

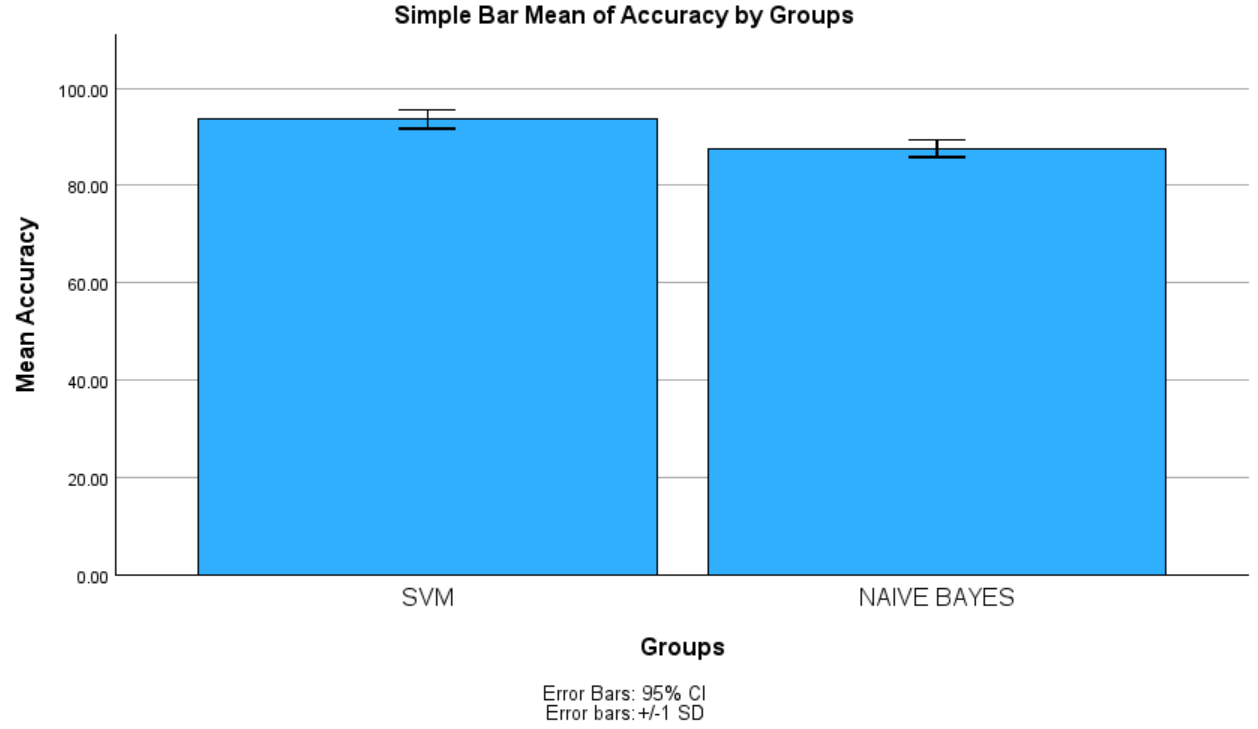
| S.0 | SVM | NAIVE BAYES |
| --- | --- | --- |
| 1 | 97.70 | 93.50 |
| 2 | 96.22 | 91.18 |
| 3 | 95.48 | 90.00 |
| 4 | 95.98 | 89.52 |
| 5 | 94.18 | 88.62 |
| 6 | 93.33 | 87.62 |
| 7 | 92.87 | 86.44 |
| 8 | 91.00 | 85.32 |
| 9 | 90.78 | 84.99 |
| 10 | 89.13 | 83.43 |

**Table-2:** Presents the statistical analysis results of the Novel SVM algorithm and the Naive Bayes 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  Naive Bayes | 10  10 | 95.4990  91.4920 | 1.53388  1.444430 | .48506  .45673 |

**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 | .037 | .850 | 6.014 | 18 | <.001 | 4.00700 | .66624 | 2.60728 | 5.40672 |
|  |  |  |  |  |  |  |  |  |  |
| Equal Variances not assumed |  |  | 6.014 | 17.935 | <.001 | 4.00700 | .66624 | 2.60692 | 5.40708 |

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