SOCIOECONOMIC ANALYTICS

Machine Learning Techniques for Classification of Stress Levels in Traffic

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How to cite this paper: Fenerich, A. T., Romanelli, E. J., Catai, R. E., Steiner, M. T. A. (2024). Machine Learning Techniques for Classification of Stress Levels in Traffic. *Socioeconomic Analytics,* 2(1), 84-93. https://doi.org/10.51359/2965-4661.2024.262686.

RESEARCH ARTICLE

Socioeconomic Analytics
https://periodicos.ufpe.br/revistas/SECAN/
ISSN Online: 2965-4661

Submitted on: 21.04.2024.
Accepted on: 25.06.2024.
Published on: 28.06.2024.

Abstract

The aim of this study is to apply Machine Learning techniques for predicting and classifying the stress level of people commuting from home to work and also to evaluate the performance of prediction models using feature selection. The database was obtained through a structured questionnaire with 44 questions, applied to 196 people in the city of Curitiba, PR. The classification algorithms used were Support Vector Machine (SVM), Bayesian Networks (BN), and Logistic Regression (LR), comparatively. The results indicate that the classification of stress levels of new instances (people) as "high" or "low" can be performed using the LR technique (presenting the highest accuracy, 83.67%).

Keywords

Artificial Intelligence; Machine Learning; physiological stress; traffic studies; Support Vector Machine; SVM; Bayesian Networks; Logistic Regression.

1. Introduction

The World Health Organization (WHO, 2017) recognizes stress as a global "epidemic," affecting over 90% of the world's population. Although it's a natural response to adverse situations, frequent stressors such as traffic irritations, overwork, lack of rest, and even an unfavorable family environment can lead individuals to imbalance their bodies, consequently leading to the emergence of other pathologies.

Stress not only directly impacts people's quality of life but also influences productivity and work quality. Occupational stress causes increased absenteeism, difficulties in work relationships, high turnover rates, and a decline in required quality standards (Zille, 2005). Therefore, companies should implement preventive measures against stress in the workplace. Moreover, since the commute between home and work is also considered an occupational period for accident characterization, supported by Law 8,213/91, Article 21, letter "D," measures against stress should also cover the time individuals spend in traffic, either going to or coming from work.

Stress is closely linked to vehicle traffic in two ways (Hoffmann, 2003): it affects people's driving behavior and is the direct or indirect causal agent of a considerable percentage of accidents. The mass circulation system itself significantly contributes to increasing stress levels. Hence, traffic-related stress can lead to accidents, termed commuting accidents if the individual is on the home-to-work route. Road Traffic Accidents (RTAs) were included in the International Statistical Classification of Diseases and Related Health Problems (ICD-10) by the WHO in 1996. The number of RTA victims is concerning due to its increasing representation, making it one of the main causes of death in Brazil and worldwide (MS, 2017; WHO, 2017). As a result, issues related to stress and traffic accidents have been extensively researched.

The relationship between stress levels during the commute to work and aggression has been studied, revealing that as stress increases, the frequency of hostility and obstructiveness also increases during the workday, particularly among male employees (Henessy, 2008). Additionally, both stress and driver aggression were higher in highly congested conditions (Hennesy and Wiesenthal, 1999). However, in highly frustrating and irritating traffic congestion, listening to music seemed to alleviate stress (Wiesenthal et al., 2000).

Research on this topic has expanded beyond mere identification and correlation of traffic-related stress with other factors or variables. Currently, it goes beyond simple descriptive and inferential statistical analyses, employing sophisticated Artificial Intelligence (AI) techniques for pattern recognition and stress level prediction (Sharma and Gedeon, 2012). Body sensors and vehicle geolocation equipment, capturing physiological signals and drivers' reactions to the operating environment, are also technologies employed for stress level prediction using machine learning (ML) (Woltermann and Schroedl, 2003; Sharma and Gedeon, 2012; Singh et al., 2013; Sun et al., 2010; Tawari et al., 2014; Deng et al., 2012), including real-time detection and classification systems (Tango and Botta, 2013; Rigas et al., 2012; Liang et al., 2007) or simulators (Rimini-Doering et al., 2001).

ML techniques, Artificial Neural Networks (ANNs), Logistic Regression (LR), and Decision Trees (DTs) have been used to build models for severity classification and, consequently, road accident prevention (Sohn and Shin, 2001). Speech classification, modeling drivers' speech under stressful conditions, has been investigated using ML techniques, specifically Bayesian Networks (BN), Support Vector Machine (SVM), and ANNs (Fernandez and Picard, 2003).

In addition to applying ML techniques for predicting and classifying drivers' stress levels during the home-to-work commute, considering attributes such as the interviewee's profile, route characteristics, company stance, and traffic stress factors, this research aims to evaluate the performance of prediction models by including the feature selection stage in the pattern recognition process. This stage can enhance predictor model performance, facilitate parameter visualization and understanding, and prevent overfitting issues (Guyon and Elisseeff, 2003).

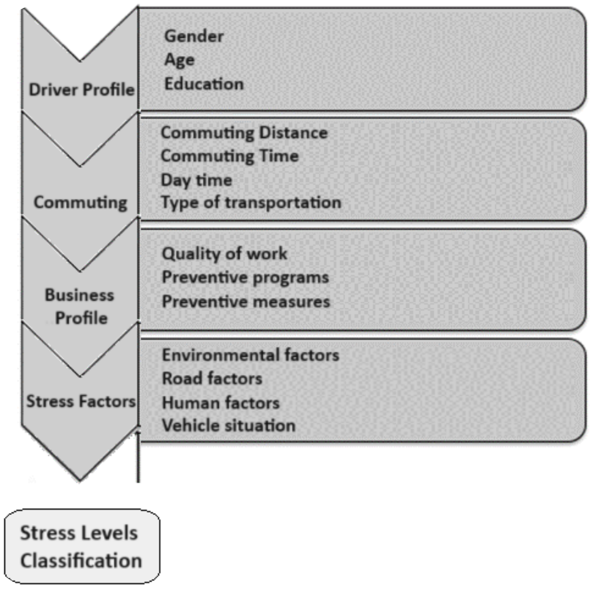
2. Problem description

The research study was conducted to gather data on the stages summarized as follows: defining attributes, designing the data collection instrument, outlining procedures for data collection, and finally, procedures for data processing and analysis. It is worth noting that all stages of the research were conducted following ethical standards.

2.1. Defining attributes

The attributes selected for the research are related to the participant's profile (interviewee; questionnaire attached); the characteristics of the home-to-work commute; the company's stance on traffic stress; and also with stressor factors (divided into eight environmental factors; twelve factors related to driving conditions; six human factors and two vehicle-related factors). In each mentioned group, attributes contributing to investigating traffic stress during the home-to-work commute were listed, as shown in Figure 1.

Figure 1 - Groups of attributes considered in the classification of traffic stress.



A total of 44 input attributes were considered, in the format of categorical variables or dummy variables, and the classification of traffic stress, corresponding to the output attribute, was defined by a binary variable (1 = "high" if the stress level ≥ 5; and 0 = "low" when the stress level < 5), as explained below.

2.2. Instrument and Data Collection

For the investigation of traffic stress classification during the home-to-work commute, a structured questionnaire consisting of closed and pre-ordered questions in five blocks of questions related to the aforementioned attributes was developed. The stress level was measured by the respondents' own perception on a scale ranging from 0 to 10.

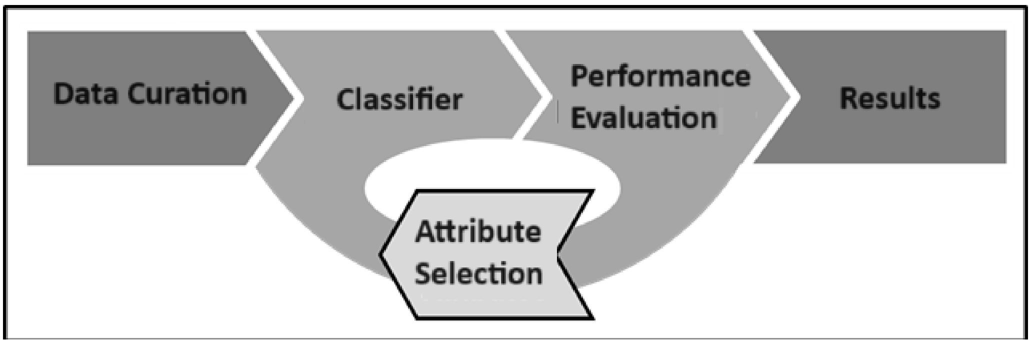
The questionnaire was made available online using the Google Forms® application, limited to people who use traffic on the home-to-work route in the city of Curitiba, PR. The questionnaire was available for collection between October and December 2016, with all 196 responses stored in the Google Drive® database. The questionnaire can still be accessed for reference purposes via the link http://goo.gl/forms/kdaO8wh1yC.

Cronbach's Alpha coefficient was used to verify the reliability of the constructs used to measure traffic stress levels, i.e., the degree to which the items that make up a scale are integrated. Using SPSS© software, the coefficient resulted in 0.827. Thus, the constructs proved reliable, as values between 0.7 and 0.9 are considered acceptable for this coefficient.

3. Methodology

The methodology consisted of data preprocessing, where the SVM, BN, and LR classification algorithms were applied comparatively, evaluating their performances. After these steps, attribute selection was performed using wrapper methods to select a subset of attributes that result in better model performance, and filter methods to rank the information gain of each attribute. Finally, the results were analyzed. These steps are summarized in Figure 2 below.

Figura 2 – Steps of Data Curation and Assessment



To process the data, continuous attributes (example: age; distance; time spent traveling; etc.) were transformed into categorical variables. The categorical attributes, with multiple response options, were transformed into dummy variables (assigning the value "0" when the interviewee does not have the characteristic and the value "1" otherwise). As an example, the attribute "Period of the day during which the route is taken", in which the interviewee can select one or more alternative answers (a. Between 6:30 and 8:30; b. Between 8:30 and 17:30; c. Between 17:30 and 19:30; d. Between 19:30 and 22:30), the coding of the dummy variable is represented by the vector (1 0 1 0) if it takes the route “a. Between 6:30 and 8:30” and “c. Between 5:30 pm and 7:30 pm.”.

The remaining attributes, originally categorical, without multiple choice options, remained unchanged. As previously mentioned, the stress level, provided initially on a scale of 0 to 10, was transformed into a binary variable, making it possible to classify it as a “high” or “low” level of stress. Table 1 presents the types of encodings used to process the data, considering each example.

Table 1 – Data processing attributes decoding examples

Attribute	Original Type	Data Type	Classes
Commuting	Continuous	Category	1 to 5 km → 1 5 to 10 km → 2 10 to 15 km → 3 15 to 20 km → 4 20 to 25 km → 5 25 to 30 km → 6 Above 30 km → 7
Day time	Multiple	*Dummies*	From 6:30 to 8:30 → 1 0 0 0 From 8:30 to 17:30 → 0 1 0 0 From 17:30 to 19:30 → 0 0 1 0 From 19:30 to 22:30 → 0 0 0 1
Stress Level (NE)	Scale (0 – 10)	Binary	“Low” → 0, if NE < 5 “High” → 1, if NE ≥ 5

Several Machine Learning techniques have been used in classification problems (Russell and Norvig, 2003). The classifier algorithms selected for the application in question are: SVM, BN and LR. First, the complete model, with 44 input attributes and 196 instances, was processed by all three classifier algorithms, thus obtaining evaluation metrics, based on the confusion matrix, to compare the prediction performance of the classification models: a) Accuracy, measured by total success rate (TAT); b) Positive predictive value, or precision, measured by the accuracy rate in “high” stress level predictions (TAA) and; c) Negative predictive value, measured by the accuracy rate in “low” stress level predictions (TAB). These metrics are given by equations (1), (2) and (3), respectively,

$$TAT = (n_{bb} + n_{aa})/n_t \quad (1)$$

$$TAA = n_{aa}/n_a \quad (2)$$

$$TAB = n_{bb}/n_b \quad (3)$$

Where onde n_{bb} represents the number of people with low levels of stress and correctly classified as “low”; $n_{aa,}$ the number of people with a high level of stress and correctly classified as “high”; n_t, the total number of instances considered (196); n_a, the total number of people with a high level of stress (145) and $n_{b,}$ the total number of people with a low level of stress

(51). Once the complete model with all attributes was constructed and tested, the feature selection stage was carried out in order to determine a parsimonious model that included only the most important predictor variables for each classifier algorithm.

There are different approaches to attribute selection methods (Blum and Langley, 1997), and in this work, the Wrapper and Filter approaches were used. The idea of the Wrapper approach is simple: the classifier algorithm is considered a “black box”, being executed with different subsets of attributes and, in the end, the subset that obtained the highest evaluation performance (Kohavi and John, 1997), also called “merit” of the best subset found. Unlike this, in the Filter approach, the selection is made independent of the classifier algorithm, and the attributes are ordered based on their scores in various statistical tests for their correlation with the output variable ((Blum and Langley, 1997), in this case, the level of stress.

After selecting the attributes using the Wrapper (Forward Selection) approach, the resulting summarized model was processed again by the classifier algorithms, thus obtaining new performance metrics, applying Equations (1), (2) and (3), for comparison between the two models (complete and summarized). The ranking of attributes in terms of information gain was also obtained using the Filter (Attribute ranking) approach. The results, both from the classifier algorithms and the selection of attributes, were obtained with the aid of the WEKA® software (Waikato Environment for Knowledge Analysis, available at: http://www.cs.waikato.ac.nz/ml/weka) and the tests performed on all classifier algorithms were applied with the cross-validation option with 10 partitions and with the default configuration for all parameters.

4. Results and Discussion

The results of the performance metrics obtained with the application of the classifier algorithms to the complete model (with all 44 attributes) are presented here; the set of attributes selected with the Wrapper approach for each of the algorithms considered; and the results obtained with the application of the classifier algorithms in the summarized model (only with the attributes selected in the feature selection stage).

4.1. Complete Model Performance Results

The highest total success rate (TAT) of the complete model was obtained with the LR algorithm, being 0.8367. In other words, the LR model can correctly predict 83.67% of the classifications made for “high” and “low” stress levels. Still considering this same algorithm, the success rate for “High” stress levels (TAA) achieved better results than the “Low” rate (TAB), these being 0.897 and 0.667, respectively. In fact, in all three classifier algorithms, TAA was greater than TAB. Among the three algorithms, the highest obtained was 0.910 considering the BN. This algorithm came in second place when considering TAT, with a result of 0.8214, followed by the worst result of 0.750 obtained when applying SVM.

4.2. Attribute Selection

For each of the three classifier algorithms, a subset of attributes with greater “merit” was obtained, that is, a model built with just a few attributes, resulting in better or equal performance to the model that considers the entire set of attributes. The number of elements in each subset with the best "merit" was four attributes, both for SVM and LR, but the elements in each subset were not necessarily the same. A larger subset was constructed for BNs, which considered a combination of six attributes as the best "merit". The description of the attributes considered in each algorithm is presented in Table 2.

Table 2 - Subset of selected attributes with the best merit for each algorithm.

Selected Atribute Subset		
SVM	**BN**	**LR**
1. Education; 2. Commuting Distance; 3. Road Factors; 4. Stress level (by human factors).	1. Age; 2. Environment; 3. Human factors; 4. Vehicle; 5. Stress Level (by human factors); 6. Stress Level (other factors).	1. Commuting time; 2. Day time; 3. Road factors (congestion); 4. Stress Level (by human factors).

As can be seen, the attributes that make up each subset can vary depending on the classifier algorithm applied, that is, the result of the wrapper approach method depends on the type of algorithm to be considered. An interesting aspect to note is that the attribute "Frequency stressed by human factors" was selected in all three classifier algorithms.

It is worth mentioning that the method used to select attributes with the wrapper approach only builds subsets of attributes and selects the one with the best merit, not ranking the attributes in this selected subset. Therefore, it is not possible to say which attribute(s) would be most relevant to the model with this result. Other methods for attribute selection perform this task, such as Information Gain Ranking, from the Filter approach, builds a ranking based on the information gain of each attribute. By coincidence, the results of this method place the attribute "Frequency with which you are stressed by human factors" in first place in the information gain ranking (0.1646), followed by the attributes "Human factors (drivers who make mistakes when driving)" , with information gain of 0.1356, and "Frequency with which you are stressed by road factors" (0.1236).

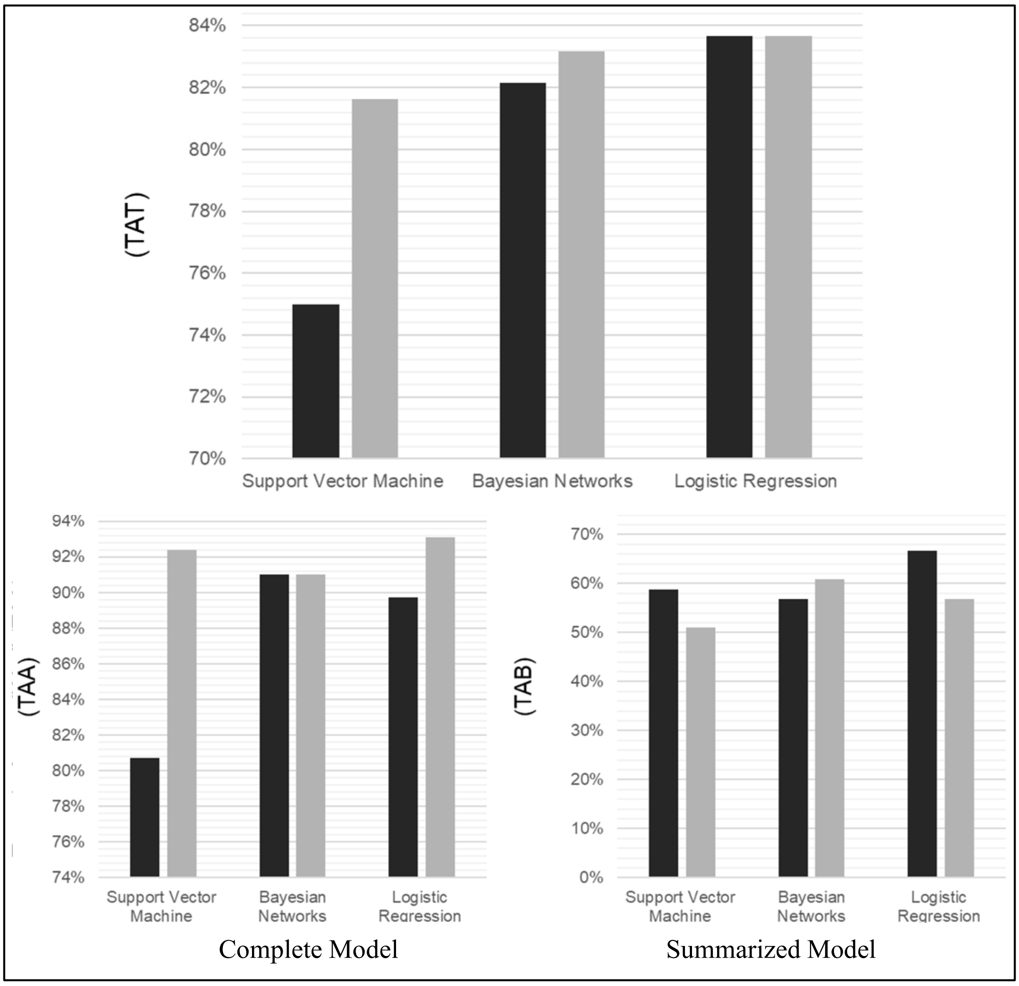
4.3. Summarized Models Performance Results

The summarized model, built only with the attributes selected for each classifier algorithm, largely obtained better success rates compared to the complete model. Only the LR algorithm had a TAT equal to the full model, 0.8367, but on the other hand, it obtained a better result for the TAA, with an increase of 3.4%. In other words, although the total success rate was the same, the prediction of success in classifying people with "high" stress levels is higher in this summarized model.

The accuracy of the summarized model achieved a significant improvement when using the SVM, being measured by the TAT, which increased from 75% to 81.63%. The TAA also improved in this model, going from 0.807 to 0.924. Even though it is not as significant an increase as what was seen in the TAT of the summarized model using the SVM, the BNs also showed an improvement in performance with the summarized model, from 0.8214 to 0.8316.

All success rates (TAT, TAA and TAB), used as model performance metrics (complete and summarized) for each classifier algorithm are shown in Figure 3.

Figure 3 – Success rates (TAT, TAA and TAB) for the complete and summarized models on each classifier.



5. Conclusion

Based on the models, the classification of the stress level as "high" or "low" can then be used to predict new instances, with a total accuracy of 83.67%, this being the highest TAT found, using of the LR classifier algorithm in both the full and summary models. However, the TAT did not present, in this case, an increase in the performance of the summarized model with the application of the attribute selection stage, the reduction in the number of attributes, from 44 to just four attributes, the increase in the prediction rate of "high" level of stress and decrease in the prediction rate of "low" level of stress, given by TAA and TAB, respectively, were considerable results, thus justifying the inclusion of this step to obtain better benefits.

Furthermore, in the other classifier algorithms, BN and SVM, the attribute selection step improved the model performance by 1.76 and 6.63 percentage points, respectively, and in both cases a significant reduction in the number of attributes considered in the summarized model in relation to the complete model. Another notable result in the attribute selection stage, in addition to the improvement in performance and reduction in the number of attributes, was the identification of the most relevant attribute for the models, “Frequency with which you are stressed by human factors”, this being the one selected in the approach wrapper by the three classifier algorithms and also the one that had the greatest information gain with the filter approach.

Conflict of Interest Declaration

The authors have no conflicts of interest to declare. All co-authors agree with the manuscript’s contents, and there is no financial interest to report.

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