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A Support Vector Machine Approach in Predicting Road Traffic Mortality in Malaysia

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Abstract – *The traffic mortality rate is the baseline through which road safety plans of a country could be evaluated. A reliable and reasonable analysis of road traffic-related injuries and their leading causes is vital to the road safety investigation, evaluation as well as policymaking. Malaysia has the third highest fatality rate from road traffic accidents in Asia as well as in Southeast Asia. Although many researchers have attempted to provide predictive models of Road Traffic Mortality (RTM) in the country, the predictions are found to be rather unsatisfactory in forecasting the causes as well as the future road fatality. It is hypothesized that the inability of the previous models to provide a good prediction of the RTM might be attributed to the complicated and non-linear data relationship of the underlying causes of road traffic accidents. A Support Vector Machine (SVM) is demonstrated to be effective in solving both classifications as well as regression problems owing to its efficacy to cater for the non-linear relationship of a dataset. The present investigation proposed the application of SVM based model variations namely the Linear, Quadratic, Cubic, Fine, Medium, as well as Coarse Gaussian-based SVM in predicting the RTM. A dataset from 1972 to 1994 was obtained from the Malaysian road traffic database. The data were trained on the SVM model variations. It was demonstrated that the Linear-based SVM model can provide a reasonable prediction of the RTM with only a 12 % error. It is, therefore, inferred that a reasonable prediction of RTM in Malaysia could be achieved through the employment of non-conventional statistical techniques.*

Keywords: Road Traffic Mortality (RTM), Support Vector Machine (SVM), accident prediction

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1.0 INTRODUCTION

Road Traffic Injuries (RTIs) are ever-increasing global health crisis that demands effective prevention for the promotion of sustainable safety. It has been reported that RTIs are the eighth leading cause of death approximately accounting to about 1.2 million disability-adjusted life years globally in 2010 (Murray et al., 2012). It is worth noting that yearly about 1.2 million people lose their lives on the roads whilst about 20-50 million people reportedly sustain non-fatal injuries as a result of road-related traffic crashes (WHO, 2009; WHO, 2013; WHO, 2018). Moreover, a high rate of road traffic mortality as well as injuries occurrences are 90% higher in the low- and middle-income countries and the burden is still increasing largely owing to the rapid urbanisation as well as motorisation (Staton et al., 2016). Consequently, it has been reported that if appropriate measures are not taken, the road traffic injuries are forecasted to become the third leading cause of death as well as injury in the year 2020 (Murray and Lopez, 1996).

In an attempt to address the burden of RTIs, many global stakeholders such as World Health Organization (WHO), Transport Research Laboratory (TRL), World Bank, and other relevant policymakers have embarked on an effort to reduce the menace of the global road death and fatalities through regulation enforcement, education and training, improvements in road safety engineering and media campaigns. While it was reported that the multiple strategies and campaign interventions have contributed to a significant reduction of RTIs in many high-income countries, the RTIs are still one of the major threats to the low- and middle-income countries to date (Porchia et al., 2014).

Malaysia is ranked 19th out of 182 countries in the world for the highest number of road traffic deaths per 100, 000 populations (Abdul Manan, 2014). The country has recorded an average of 6,300 road fatality cases annually from 1995 to 2018. The country is classified as a middle-income nation that has recorded a population of over 32 million in the year 2017, and over 28 million numbers of vehicles were registered (JKJR, 2018). The increasing number of population, as well as registered vehicles, have led to the risk of road accidents. The Department of Statistics Malaysia (2018) stated that transport accidents were among the top five Malaysian leading causes of death in 2017.

Although road safety plans were implemented to reduce the number of RTM, Malaysia has not yet succeeded in achieving the desired set target (Darma, 2017). Different models have been developed through the usage of a variety of statistical analysis techniques to predict road accident in Malaysia. Among the prominent models are the Negative Binomial Regression Model (NBRM), Generalized Estimating Equation (GEE), as well as the Auto-Regressive Integrated Moving Average (ARIMA) model.

The employment of NBRM to predict the occurrence of motorcycle accidents per kilometre on the Malaysian primary road was investigated by (Abdul Manan et al., 2013). Some road traffic indicators namely, average daily traffic and a number of access points per kilometre with their association to motorcycle accidents were studied. It was demonstrated that the indicators could contribute to a certain extend forecast the occurrence of motorcycle accidents. However, the study was merely based on simulation as such actual comparisons with the real data were not considered. Danlami et al. (2017) applied GEE to forecast road accident fatality in Malaysia. The authors considered a number of exposure variables that comprised of a population, road length, vehicles involved in crashes as well as mobile cell subscription per 100 people in the estimation of road fatality. Dataset from the year 1974 to 2010 was used to establish the model. Although it was demonstrated that the model could provide a reasonable prediction of road fatality based on the variables examined, the figures predicted in 2015 were rather high as compared to the actual fatality recorded (difference of 1,472).

Over the years, the ARIMA is the most popular in time series techniques that were used in predicting Malaysian road accidents. ARIMA was used to model the proportion of death due to the traffic crashes in examining the effectiveness of the Motorcycle Safety Program (MSP) and economic status in reducing motorcycle accidents (Law and Radin Sohadi, 2004). The transfer function analysis of ARIMA was used to generate the pre-whitened Gross Domestic Product (GDP), Motorcycle Safety Program, population and registered vehicle to unit changes in the death series. The result revealed that the combination of low GDP and implementation of MSP had also lowered the number of registered vehicles and therefore further lowered down the number of motorcycle accidents. It was inferred from the study that the safety intervention program adopted in the country was able to reduce traffic deaths significantly.

Conversely, Law et al. (2005) carried out a projection of the vehicle ownership rate to the year 2010 from the year 2001. Then the projection was used to predict the road accident death index in 2010. The result was seen to suit the Malaysia road safety target in 2001 which was set to achieve a total of 4 road accident deaths per 10,000 registered vehicles by 2010. The road death index in 2010 was 3.4 per 10,000 registered vehicles. Therefore, it was erroneously assumed that the 2001 safety plan was achieved. The subsequent 2006 Malaysia road safety plan targeted an index of 2.0 road accident deaths per 10,000 registered vehicles by the year 2010, and therefore, this prediction was seen to be inaccurate.

It could be seen that the prediction of RTM in Malaysia has received numerous attention from many researchers both in the past and present. However, as noted earlier many such predictions fell short in fitting the model with the data previously employed by the preceding researchers and as such fails to mitigate the problem of predicting RTM with a set of non-linear data. In response to this problem, the current study is motivated toward considering other statistical techniques that could provide an alternative for the prediction of road mortality with regards to the Malaysian accident's historical data.

Machine learning is an application of artificial intelligence that has the ability to automatically learn and improve from experience without being explicitly programmed; therefore, it is effective in predicting future performance. Furthermore, a variety of machine techniques have been used widely in other research fields such as sports engineering, production engineering, and even health monitoring (Binetti et al., 2017; James et al., 2018; Musa et al., 2019; Yusri et al., 2018). The application of machine learning in a variety of fields is increasingly becoming popular due to the ability of the algorithm to solve a non-linearity problem of a data set. It is also worth noting that machine learning algorithms have also been successfully applied in the area of traffic safety. Some machine learning techniques have been used in mimicking driver behaviour to avoid collision or congestion (Cai et al., 2015; Huang et al., 2018), developing traffic flow and traffic congestion model (Arif et al., 2018; Sekuła et al., 2018), and accident prediction (Iranitalab and Khattak, 2017; Lin et al., 2015).

In the Malaysian perspective data, a particular study has employed an Artificial Neural Network (ANN) algorithm in predicting road death (Ramli, 2011). The authors utilised the number of registered vehicles, population, road length as well as road system in developing the ANN model. Although, some promising results were found, nonetheless, the authors only focused on a selected black spot area in Kluang, Johor. Radzuan et al. (2019) also employed

ANN algorithm in their study but the analysis is on predicting serious injury by taking national accident data. To date, not many studies has thus far attempted to predict the occurrence of road accident through the employment of machine learning algorithms concerning all Malaysian data. Therefore, the present study is aimed at developing a machine-based predictive model of the RTM in Malaysia using parameters from the Malaysian data of road accident occurrences (the number of registered vehicles, population, road length as well as road system). The study is endeavoured to apply the non-conventional data analysis technique named Support Vector Machine (SVM) in the prediction of road traffic mortality in Malaysia.

2.0 METHODOLOGY

This section will discuss the general description of the methodology of the study and the data that is used in this study. All the statistical analysis was carried out by means of MATLAB® 2016b (MathWorks Inc., Natick, USA).

2.1 Dataset

The dataset of the present study was obtained from the previous research carried out by Radin Sohadi (2005) from the year 1972 to 1994. These data were used as a training set for model development. Another dataset from 1995 to 2018 was taken from JKJR (2018) for the validation part. The dataset consists of four parameters: the number of registered vehicles, population, total road length, and road system (the inclusion or the exclusion of East Malaysia, where prior to 1981, the dataset only accounts for dataset available from only the Peninsular Malaysia).

2.2 Support Vector Machine Kernel Functions

The outcome of this study is observed response predictions by providing supervised learning of several independent variables. The SVM algorithm is selected to perform the regression analysis. SVM is best used for classification if the outcome is a categorical type however it is also good to predict a regression if the outcome is numerical date type (Vapnik, 2013).

MATLAB® 2016b has set up applications for six kernel functions of SVM. SVM can be divided into two categories which are the vector is linear SVM or the vector is non-linear SVM (Polynomial, i.e. Quadratic and Cubic SVM; Gaussian Radial Basis Function, i.e. Fine, Medium, Coarse SVM). The best-suggested kernel functions would be the one that suggesting a small error and presenting a hyperplane that its margin size tolerable to the error. The mathematical formula of these kernel functions used in this study is described by Nakano et al. (2017) and Taha et al. (2018). Once the images were traced in Adobe Photoshop, they were loaded in MATLAB. The global threshold was calculated from the imported grayscale using Otsu's method. Then, the greyscale image was converted to a binary image based on the previously calculated threshold.

2.3 Model Evaluation

The model was evaluated by means of R squared (R^2), mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE).

The R^2 is an indicator that is commonly employed to ascertain how well one or more features describe a target value. In the present investigation, the R^2 is used to evaluate the overall effect of accidents related variables on the RTM prediction. It is worth noting that the value of R^2 ranges from 0 to 1. The closer the value is to 1 the stronger the degree of the interpretation and vice versa. The R^2 is computed in the present study using the formula shown in Equation (1), where n refers to the number of samples, $\hat{y}_i$ represents the actual RTM value of the i-th sample, yi serves as the predicted value whilst $\bar{y}$ represents the mean of all the predicted values.

$$R^2\,(y,\hat{y}) = 1 - \frac{\sum_{i=1}^{n}(yi-\hat{y}i)^2}{\sum_{i=1}^{n}(yi-\bar{y})^2} \tag{1}$$

The MAE is the average of the absolute values deviated between the predicted and the actual values. It should be noted that as the deviation is absolute as such, the negative, as well as the positive offset, is often a trade-off. It is worth to mention that the MAE is not sensitive to the existence of anomalies. However, it serves useful in the projection of the actual error of a prediction. The generalised equation for the calculation of MAE is given in Equation (2), where n is the number of samples, y_i and $\hat{y}i$ is the actual RTM and that predicted by the model for the i-th years.

$$MAE = \frac{1}{n}\sum_{i-1}^{n}|(y_i - \hat{y}_i)| \tag{2}$$

The MAPE is a measure of the total error for the predictive model. It is defined as the average of the absolute value of the relative error. Equation (3) provides the mathematical expression for the determination of MAPE. In the equation, n represents the number of samples whilst the re-err accounts for the relative error.

$$MAPE = \frac{1}{n}\sum_{i-1}^{n}|(re - err)| \tag{3}$$

The RMSE is a measure that is often used to assess and compare the predictive error of a model. It is the standard deviation of the residuals which explained how concentred the data is accumulated around the line of best fit. The lower the RMSE value, the better the forecasting ability of a model with respect to its absolute deviation. Nonetheless, it should be noted that the presence of a few large errors could lead to a larger value of RMSE. The Generalized equation for RMSE is given in Equation (4), where f represents the forecasts or the expected values whilst the o represents the observed values or the known results.

$$RMSE = \sqrt{\overline{(f-o)^2}} \tag{4}$$

3.0 RESULTS

Table 1 projects the comparative effectiveness of the SVM model variations in the prediction of RTM. It could be observed from the table that all SVM variation models give a good prediction of given independent variables as the R2 is near to 1. However, the Linear SVM variation model has outperformed the other SVM variations in the prediction of the RTM comparatively across all the performance evaluation metrics. Moreover, it is worthwhile to note that the mean absolute percentage error obtained by the Linear SVM model is the lowest amongst others with 12% accuracy. This finding has portrayed the ability of the selected feature, i.e. the number of registered vehicles, population, road length as well as road system in the prediction of the road traffic mortality in Malaysia.

Table 1: Performance evaluation of the developed SVM model variations

Evaluation Metrics	Linear	Quadratic	Cubic	Fine Gaussian	Medium Gaussian	Coarse Gaussian
R Sq	0.95	0.93	0.97	0.94	0.96	0.94
RMSE	209.59	254.78	225.95	429.11	328.76	447.29
MSE	43927	64911	51054	184130	108080	200070
MAE	170.92	185.57	181.09	304.96	247.09	344.30
MAPE %	12 %	16 %	4673 %	16 %	15 %	15 %

Figure 1 illustrates the comparative analyses of the predictive efficacies of the evaluated SVM variation models. It could be seen from the figure that all SVM variations were able to reasonably pick up the trends closely with the actual road death across the years observed except Cubic SVM. This finding has additionally indicated that the Cubic model has not performed well and cannot be used for forecasting the Malaysian road mortality with regards to the variables examined in the present study.

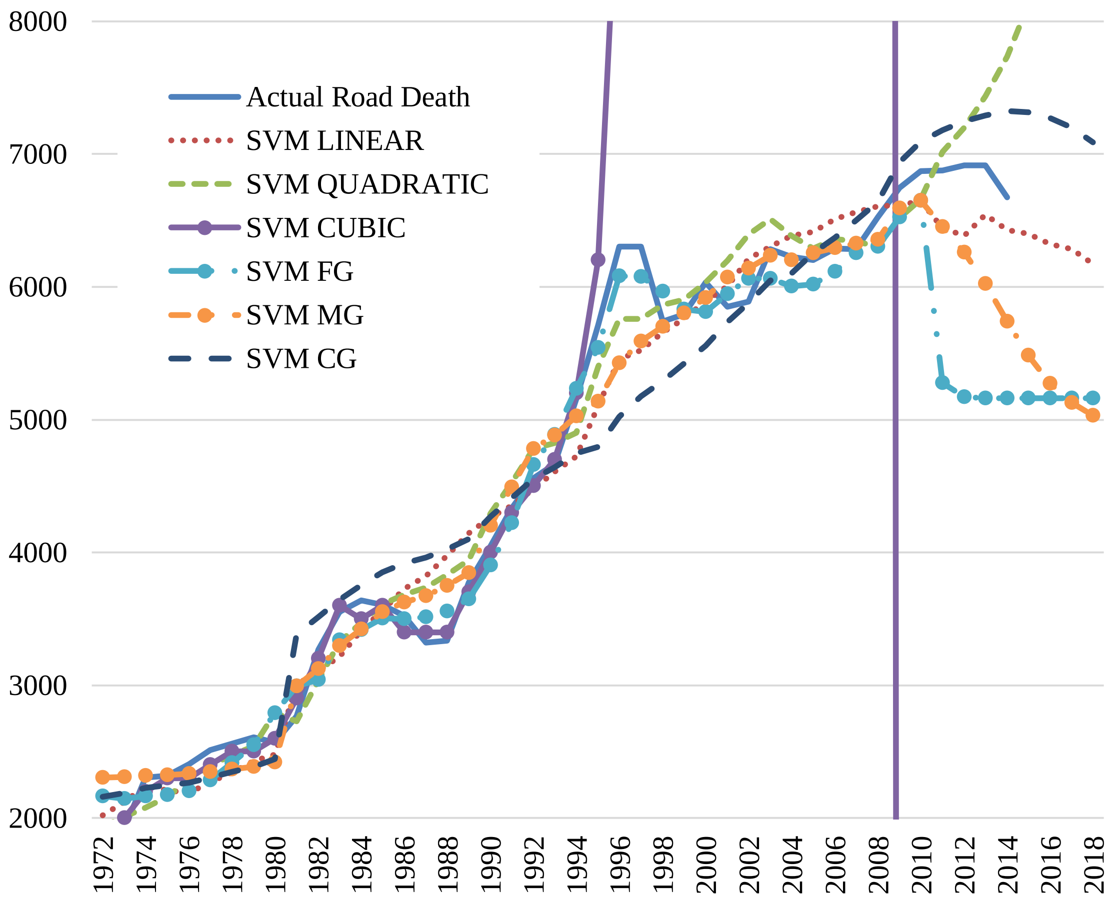

Figure 1: Comparative analysis of the actual and predicted road traffic mortality across all the tested SVM model variations

4.0 DISCUSSION

The present investigation aimed to propose an alternative means of predicting RTM using a variety SVM model variations from a selected road accident-related data viz. the number of registered vehicles, population, road length as well as a road system. It was established from the analysis of the historical data gathered (1972-2018) that a good prediction of RTM could be achieved with respect to the investigated variables. Moreover, the Linear SVM based model variation is shown to be a better model of predicting the RTM as compared to the other tested model variations. It is worth noting that although several studies have explored the use of aforementioned accident-related variables in Malaysia, nonetheless, the present study is the first of its kind to investigate an alternative means of predicting the RTM utilizing a machine algorithm particularly a variation of SVM models to fit in the dataset of the country. Consequently, the variables utilized in developing the model of the present study are non-trivial in contributing to the occurrences of RTM in the country.

Table 1 demonstrates the performance ability of the various SVM model variations evaluated in this investigation. It could be seen that all the models have accounted for approximately an overall R2 ranging from 93 to 97 %. The predictive ability provided by the present developed SVM models are non-trivial as in all the SVM variations, the R2 exceeded 0.90 for training as well as the testing. The results of the training of these models have shown that the model could be effective in providing a reasonable prediction of the RTM using the Malaysian road accident data. The previous researchers have documented that the R2 associated with regression models is an indicator that describes whether the features could reasonably describe the target variables (Binetti et al., 2017; Deb et al., 2016; Witek-Krowiak et al., 2014). The closer the value of the R2, the stronger the degree of the prediction as well as the reliability of the interpretation of the model prediction. This finding has further shown the efficacy of the SVM model variations in its ability to cater to the non-linearity behaviour of the dataset.

It has been previously reported that the increase in a road accident is largely attributed to the rapid growth in the population of the country owing to the economic factors such as industrialization as well as motorisations (Masuri et al., 2017). The findings of this study are in agreement with previous researchers who inferred that increase in vehicle ownership as a result of economic growth has a corresponding upsurge in the population rise in the country which accounted for rapid development of the country's population in conjunction with steady occurrence of accident for the past 40 years (Danlami et al., 2017). Moreover, the previous study has demonstrated that road accident fatality could be effectively managed in the event that these two variables are addressed (Persia et al., 2015). On the other hand, mortality rates have shown to decline with an increasing number of vehicles involved in a crash per kilometre of the road (Danlami et al., 2017). Therefore, it could be ascertained that road length may also be a potential exposer of RTM from a Malaysian perspective. Overall, a better prediction ability is achieved in the present investigation with respect to the accident-related variables assessed. The prediction of RTM in this study has accounted for only 12% mean absolute percentage error as opposed to 197% reported in a previous study that utilised the same dataset (Radin Sohadi, 1998).

5.0 CONCLUSION

The result of the current investigation has demonstrated that SVM model variations of machine learning-based algorithms are able to provide a good prediction of the RTM. The Linear variation of the SVM model has rather demonstrated an exceptional prediction efficacy in comparison to the other tested model variations. However, the Cubic-based variation of the SVM is shown to be unsuitable for the prediction of the RTM in the present investigation. Moreover, it was shown from the study that the accidents related variables investigated, i.e. the number of registered vehicles, population, road length as well as road system could be a potential cause of RTM in Malaysia. Consequently, the present investigation has demonstrated that the road accident-related data in Malaysia might be a complicated non-linear and therefore a prediction of RTM could be reasonably attained when a non-conventional statistical technique is employed. The results from the present investigation might be essential when defining a feasible road safety target in the country. The proposed technique could be used both to forecast as well as to measure retrospectively the success of the road traffic safety improvement and to ascertain whether more pertinent efforts are required in order to attain the predetermined road safety targets in the country.

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