An Efficient Analysis of Road Accidents Severity Using Novel Support Vector Machines Over Artificial Neural Networks with Improved Accuracy Rate

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Abstract

Aim: To perform an efficient analysis of road accidents severity prediction using Support Vector Machine and Artificial Neural Network algorithms. Materials and Methods: Road accident severity prediction is performed by Support Vector Machine algorithm (N=10) and Artificial Neural Network algorithm (N=10) using Traffic-crashes dataset. Results and Discussion: The road accident severity prediction using Support Vector Machine algorithm (Accuracy 83.6\%) and with Artificial Neural Network algorithm (Accuracy 73.3\%). There is no significant difference between the groups. Conclusion: Within the limits of this study, SVM algorithm has significantly better accuracy than ANN algorithm.

Key-words: Machine Learning, Computer Vision, Novel SVM, Road Accident Severity Prediction, Artificial Neural Networks.

1. Introduction

Road accident severity prediction is the process of predicting the severity measure of accidents. In recent years, the road accident has become a major problem and marked as ninth prominent cause of deaths in the world (Labib et al. 2019). It is estimated from a study (“Road Traffic Injuries” n.d.) that 1.3 million people died and a large number of people got injured in 2019 around the world. An efficient and accurate accident severity prediction can help to provide vital information...
for emergency service providers to evaluate the severity level of accidents, estimate the potential impacts and proceed with the efficient accident management.

Road traffic accident severity prediction has been carried out by researchers and 20 related research articles in IEEE Digital Xplore and 15 articles are published in Research gate. (Bharti Sharma, Katiyar, and Kranti Kumar 2016) analyzed the urban traffic accidents using the Support Vector Machine algorithm. (Alkheder, Taamneh, and Taamneh 2017) used Artificial Neural Networks to predict the severity of around 6000 accidents that occurred in AbuDhabi during 2008 to 2013. (Jacobé de Naurois et al. 2019) used Artificial Neural Networks to detect driver drowsiness level and predict when the state of the driver will be impaired. (Zhang et al. 2018) used Decision trees, Random forest, KNN and ANN algorithms to predict accident severity. The ANN and Random forest produced better results with accuracy rates of 52.9% and 53.9% respectively. (García de Soto and Bumbacher 2018) used SVM models to predict accident severity and they have given clear explanations about accident severity prediction with more accuracy.

Previously our team has a rich experience in working on various research projects across multiple disciplines (Sathish and Karthick 2020; Varghese, Ramesh, and Veeraiyan 2019; S. R. Samuel, Acharya, and Rao 2020; Venu, Raju, and Subramani 2019; M. S. Samuel et al. 2019; Venu, Subramani, and Raju 2019; Mehta et al. 2019; Sharma et al. 2019; Malli Sureshbabu et al. 2019; Krishnaswamy et al. 2020; Muthukrishnan et al. 2020; Gheena and Ezhilarasan 2019; Vignesh et al. 2019; Ke et al. 2019; Vijayakumar Jain et al. 2019; Jose, Ajitha, and Subbaiyan 2020). Now the growing trend in this area motivated us to pursue this project.

In the existing system, the data considered to predict the accident severity does not contain functional features like weather and lighting conditions which tend to increase the severity of accidents in major cases. It is important to include the features like weather and lighting conditions. So, this research focuses on considering these conditions along with other factors that help in predicting accident severity using Support Vector Machine algorithm with better accuracy.

2. Materials and Methods

The study setting of the proposed work is done in Saveetha School of Engineering, SIMATS. The number of groups identified for the study is two. The group 1 is Artificial Neural Networks and group 2 is Support Vector Machines. Using G power 10 sample sizes and totally 20 sample sizes have been carried out for our study, 95% confidence and pretest power 80% (Chong, Abraham, and Paprzycki 2005).
The dataset named ‘Traffic-Crashes’ is downloaded from a public domain. The data in the dataset is about the traffic accidents that occurred in the Las Vegas region in the year 2016. The data was preprocessed and all the null values and unwanted columns have been removed from the dataset. The dataset includes information about the condition of the driver, weather (rainy, cloudy, clear) and lighting condition (dark, day, dull). The dataset was split into two parts namely the training part and the testing part. 90% of the data was used for training and the remaining 10% was used for testing. The algorithms were implemented by evaluating the train and test sets.

Fig 1 represents the framework of predicting the severity of an accident step by step. The input is given from the records that are present in the dataset by reading the dataset into the program. Using Support Vector Machines and Artificial Neural Networks, the input is processed and the data is divided into training and testing parts. In this case, 90% of the data is used for training and the remaining 10% is used for testing.
SVM classifier is used to train the data and the Sequential class of ANN is used to add hidden layers that are connected to the input layer and train the data. The function predict() which is present in Sequential and SV Classifier classes is used to predict the output of the testing data. The predicted output is the accident severity and it is displayed as either Moderate Accident or Severe Accident.

**Artificial Neural Network Algorithm - Group-1**

Pseudocode for ANN algorithm is given in Table-1. Artificial Neural Network algorithm is a deep learning based algorithm. As the name suggests, this algorithm is inspired by human brains and it learns as the human brain learns. Neural network consists of an input layer, hidden layers and an output layer to predict and store the output.

| Table 1 - Pseudocode for ANN Algorithm |
|----------------------------------------|
| // I : Input dataset records           |
| 1. Import the required packages.       |
| 2. Convert the string values in the dataset to numerical values. |
| 3. Assign the data to X_train, y_train, X_test, y_test variables. |
| 4. Using train_test_split() function, pass the training and testing variables and give test_size and random_state as the parameters. |
| 5. Import the Sequential() class.      |
| 6. Using Sequential() class, add input layer, hidden layers, output layer. |
| 7. Predict the output using.predict() function. |
| 8. Calculate accuracy and other measures of the model from the confusion matrix. |
| **Output**                             |
| // Accident Severity                   |
The activation function known as Transfer Function used here in the input and the output layers is ‘relu’ which is a Rectified Linear Unit. The optimizer is set as ‘adam’. It is the mostly used and best stochastic gradient descent function. The hidden layer is interconnected to the input layer and connected to the output layer where the output is stored.

**SVM Algorithm - Group 2**

Pseudocode for SVM Algorithm is given in Table-2. Support Vector Machine Algorithm is a supervised machine learning algorithm. It is a classification algorithm that performs data classification by forming a hyperplane between the data points existing in the plane. The hyperplane will try to be as far away from both the data points. The kernel function that is used in the SVM Classifier here is ‘linear’ as our data can be linearly related.

| Table 2 - Pseudocode for SVM Algorithm |
|----------------------------------------|
| // I : Input dataset records           |
| 1. Import the required packages.       |
| 2. Convert the string values in the dataset to numerical values. |
| 3. Assign the data to X_train, y_train, X_test, y_test variables. |
| 4. Using train_test_split() function, pass the training and testing variables and give test_size and the random_state as parameters. |
| 5. Import the SVClassifier from sklearn library. |
| 6. Using SVClassifier, predict the output of the testing data. |
| 7. Calculate the accuracy and other metrics of the model from the confusion matrix. |
| **Output**                             |
| // Accident severity                   |
The software tool used to evaluate ANN and SVM algorithms is Kaggle in Python programming language. The hardware configuration includes an intel i3 processor with a RAM size of 4GB. The system used was 64-bit Windows 10 Operating System.

**Statistical Analysis**

For statistical implementation, the software tool used here is IBM SPSS V26.0. Statistical Package for Social Sciences is used for calculating the statistical calculations such as mean, standard deviation, significance and also to plot the graphs etc.,. The independent variables are weather_condition, driver_condition and lighting and the dependent variable is ‘result’ (which describes the severity of accidents in numerical form). In SPSS, the datasets are prepared using 10 as sample size for each group and Accuracy is given as the testing variable.

3. Results

The accuracy and F1_Score measured for different samples using Artificial Neural Network algorithm is given in Table 3. Table 4 shows the accuracy and F1_Score measured for different samples using Support Vector Machine algorithm. Table 5 shows various statistical measures like Accuracy, Precision, Recall and F1-Score calculated using the confusion matrix in the program implementation. The confusion matrix is a 2x2 matrix containing True Positive(tp), True Negative(tn), False Positive(fp), False Negative(fn).

| Test | Accuracy | F1_Score |
|------|----------|----------|
| Test 1 | 71.00 | 83.00 |
| Test 2 | 71.00 | 83.00 |
| Test 3 | 70.00 | 82.00 |
| Test 4 | 81.00 | 89.52 |
| Test 5 | 69.00 | 81.65 |
| Test 6 | 70.00 | 82.35 |
| Test 7 | 76.00 | 86.36 |
| Test 8 | 74.00 | 85.05 |
| Test 9 | 75.00 | 85.71 |
| Test 10 | 76.00 | 86.36 |
Table 4 - Accuracy of Road Accident Severity Prediction Using SVM Algorithm
(Mean Accuracy = 83.60, Mean F1_Score = 88.76)

| Test  | Accuracy | F1_Score |
|-------|----------|----------|
| Test 1| 79.00    | 86.27    |
| Test 2| 86.00    | 90.66    |
| Test 3| 83.00    | 88.59    |
| Test 4| 85.00    | 91.12    |
| Test 5| 81.00    | 86.71    |
| Test 6| 83.00    | 88.88    |
| Test 7| 81.00    | 88.05    |
| Test 8| 83.00    | 89.03    |
| Test 9| 82.00    | 88.88    |
| Test 10| 83.00  | 89.44    |

Table 5 - Calculation of Performance Measures Using Confusion Matrix
(Accuracy of SVM 84% is More Compared to ANN 74%)

| Measure | Support Vector Machine (SVM) | Artificial Neural Network (ANN) |
|---------|------------------------------|---------------------------------|
| Accuracy| 84.00                        | 74.00                           |
| Precision| 89.18                       | 100.0                           |
| Recall  | 86.84                        | 74.00                           |
| F1-Score| 88.00                        | 85.05                           |

Table 6 shows group statistics results. For Independent Samples tests we take equality means for every group and parameters. F-score and Significance is calculated for Levene's Test, Equality of Variances are taken. Whereas for t-test equality means are calculated. This includes Significance, Mean Difference for each group, standard deviation for variance assumed and not assumed values. Confidence interval of the difference as lower and upper values range as shown in Table 7.
Table 6 - Group Statistics Results (Mean of SVM 83.60 is more Compared to ANN 73.30 and Standard Error mean for SVM is 0.63 and ANN is 1.19)

| Groups   | N  | Mean   | Std. Deviation | Std. Error Mean |
|----------|----|--------|----------------|-----------------|
| Accuracy | ANN| 10     | 73.3000        | 3.77271         |
|          | SVM| 10     | 83.6000        | 2.01108         |
| F1_score | ANN| 10     | 84.5000        | 2.52501         |
|          | SVM| 10     | 88.7630        | 1.51581         |

Table 7 - An Independent Samples t Test of Accuracy for Predicting Accident Severity Using SVM and ANN algorithms. SVM Algorithm Appears to Perform Significantly Better than ANN Algorithm. (p=0.001)

|              | F     | Sig | t      | df | Sig(2-tailed) | Mean Difference | Std. Error Difference | Lower    | Upper    |
|--------------|-------|-----|--------|----|---------------|-----------------|----------------------|----------|----------|
| Accuracy     | 5.080 | .037| -6.879 | 18 | .001          | -9.30           | 1.35195              | -12.14035| -6.45    |
|              |       |     |        |    |               |                 |                      |          |          |
|              |       |     |        |    | Equal Variances assumed |                 |                      |          |          |
|              |       |     |        |    | Equal Variances not assumed |                 |                      |          |          |
| F1_Score     | 4.173 | .051| -4.577 | 18 | .001          | -4.263          | .93131               | -6.21961| -2.30    |
|              |       |     |        |    | Equal variances assumed |                 |                      |          |          |
|              |       |     |        |    | Equal variances not assumed |                 |                      |          | -2.27    |

Figure 2 is a bar graph that is plotted by selecting Mean Accuracy on Y-axis and the Groups on X-axis. From the graph, it is clear that SVM has significantly higher accuracy than ANN. The error bars are shown in the graph and the error rate is less for SVM compared to ANN.
The sample data is tested statistically using the SPSS tool with group ID-1 is ANN algorithm and group ID-2 is SVM algorithm. In this study, it is observed that the SVM algorithm proved with better significant results and improved accuracy than the ANN algorithm.

4. Discussion

In this study, we observed that Novel SVM algorithm has better significant accident severity prediction accuracy and error difference than ANN algorithm (p<0.005, Independent Sample t test). The improved accuracy and reduced Loss for SVM (mean accuracy = 83.60%, mean Loss=5.47%) than ANN (mean Accuracy = 73.30%, mean Loss=10.39%).

Various machine learning algorithms are used to predict accident severity. ((Chong, Abraham, and Paprzycki 2005) used SVM and hybrid tree-networks to predict accident severity. Out of which, the hybrid decision-tree neural network produced better and accurate results compared to the other algorithms. (García de Soto and Bumbacher 2018) used neural networks to predict accident severity. This model is compared with Decision trees and Multilayer perceptron (MLP). (Pradhan and Ibrahim Sameen 2020) used neural networks and support vector machines to determine the factors that greatly affect the severity of driver injuries caused by traffic accidents. (Mokhtarimousavi et al. 2019)
investigates the prediction of work zone crash severity and the contributing factors by using support vector machine algorithm. (Z. Li et al. 2012) developed an SVM model (48.8%) for analysing crash injury severity and it is compared with ordered probit model (44.0%). SVM and Negative Binomial regression models are used to predict motor vehicle crashes (X. Li et al. 2008) and it is found that SVM models effectively and accurately predicted crash data.

Our institution is passionate about high quality evidence based research and has excelled in various fields ((Vijayashree Priyadharsini 2019; Ezhilarasan, Apoorva, and Ashok Vardhan 2019; Ramesh et al. 2018; Mathew et al. 2020; Sridharan et al. 2019; Pc, Marimuthu, and Devadoss 2018; Ramadurai et al. 2019). We hope this study adds to this rich legacy.

The limitation in our study is that this proposed model takes longer execution time for preprocessing. In the future, this limitation can be overcome by optimizing this algorithm to work faster.

5. Conclusion

Support Vector Machine algorithm has significantly greater accuracy than the Artificial Neural Networks. The accuracy which we achieved using the algorithm is a good score in predicting accident severity.

Declarations

Conflict of interests

No conflict of interest in this manuscript.

Authors Contributions

Author U. Sravan Kumar was involved in data collection, data analysis, manuscript writing. Author R. Beaulah Jeyavathana was involved in conceptualization, data validation, and critical review of manuscript.
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