Comparative Study of PSO-ANN in Estimating Traffic Accident Severity

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Summary
Due to Traffic accidents people faces health and economical casualties around the world. As the population increases vehicles on road increase which leads to congestion in cities. Congestion can lead to increasing accident risks due to the expansion in transportation systems. Modern cities are adopting various technologies to minimize traffic accidents by predicting mathematically. Traffic accidents cause economical casualties and potential death. Therefore, to ensure people's safety, the concept of the smart city makes sense. In a smart city, traffic accident factors like road condition, light condition, weather condition etcetera are important to consider to predict traffic accident severity. Several machine learning models can significantly be employed to determine and predict traffic accident severity. This research paper illustrated the performance of a hybridized neural network and compared it with other machine learning models in order to measure the accuracy of predicting traffic accident severity. Dataset of city Leeds, UK is being used to train and test the model. Then the results are being compared with each other. Particle Swarm optimization with artificial neural network (PSO-ANN) gave promising results compared to other machine learning models like Random Forest, Naïve Bayes, Nearest Centroid, K Nearest Neighbor Classification. PSO- ANN model can be adopted in the transportation system to counter traffic accident issues. The nearest centroid model gave the lowest accuracy score whereas PSO-ANN gave the highest accuracy score. All the test results and findings obtained in our study can provide valuable information on reducing traffic accidents.

Key words:
Machine learning model, Traffic accident severity, Particle swarm optimization, Hybrid artificial neural network, Prediction accuracy

1. Introduction

Traffic accident has already become a matter of concern for the human being. Many losing their life due to this disastrous incident. Life is becoming harder day by day for the people. An accident not only causes huge damage to a family but also affects the economy of a country. Sometimes accidents become a barrier between the developments of a country and eventually cause great damage globally. Many developed countries depend largely on on-road transportation. The European economy is also very much dependent on on-road transportation. Traffic accidents act as resistance to the normal day to day life [1]. Malaysia faces 24 deaths among every 100,000 people which is a very increased number [2]. According to world statistics, the total number of fatalities in 2016 was 1,350,000. In Africa, the number was 246,719. In Europe 85,629. In America 153,789, In South-east Asia 316,080, In Western Pacific 328,591 [15]. In the UK the fatality number was 2,019. And these were only the record if 2016. Road accidents and incidents are occurring on a regular basis. Road accidents may occur for various reasons. It may occur due to driving carelessly, traffic rules violation and most importantly the increased number of vehicles [3]. It has become a tough job to reduce accidents as the population is increasing every day. The more the population grows, vehicles will increase too. But we can reduce the damage of accidents by taking necessary steps quickly. If the help can arrive on time, the damage can be reduced, the injured can be rescued and even lives can be saved. A method was proposed in this study to detect the severity of an accident. The method is a hybridized method of Particle Swarm Optimization and Neural Network to gain a better performance. The technique outperformed some other machine learning techniques. By predicting the severity of an accident, we can provide help to the injured.

2. Related Work

Many types of research have been done to predict the severity of the traffic accident. In reference [4], using Recurrent Neural Network was improved of traffic accident severity prediction based on 1130 accident data that had been occurred on the North-South Expressway (NSE), Malaysia during six years from 2009-2015. The RNN model got an accuracy of 71.77%. On the other hand, MLP and BLR models gained an accuracy of 65.48% and 58.30% respectively. Therefore, the model of RNN, which showed better results considering MLP and BLR models.

Another research in [5] where two models were used ordered probit model and ANN. The probit model is a type of regression model which is accustomed to analyzed the relationship between categorical response variables including predictive variables that are numerical,

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categorical or a combination of both variables [6]. In reference [5], the ordered probit model showed 59.5% accuracy which was less than the ANN model and the ANN model accuracy value was 74.6% for severity prediction of the traffic accident.

Another research in [7], for traffic accident severity prediction where three classification approaches were applied: Random Forest, ANN, and SVM. The Random Forest got an accuracy of 80.6% whereas the ANN and SVM models achieved an accuracy of 61.4% and 54.8% respectively. Therefore, Random Forest will be an obvious choice for predicting the severity of the traffic accident as its decision-making process is more reliable.

In another research on traffic accident severity prediction, Bayesian networks performed better than the regression model [8]. Bayesian networks are more useful when it comes to predicting the severity.

In another research, the TASP-CNN model which showed better performance for traffic accident severity prediction. That study focused on calculating weights of each feature of the traffic accident and FM2GI algorithm, which is the conversion of the feature matrix to a gray image. The process is to convert a single feature relationship from the accident dataset into gray images and then combine it in parallel as an input variable to test or train the model [9].

In this research paper, Particle Swarm Optimization was hybridized with an Artificial Neural Network in order to predict accident severity. In 1995 Particle Swarm Optimization (PSO) was introduced by Kennedy and Eberhart [10]. PSO adapts behavioral patterns of birds flocking and fish schooling as to guide the particles to search efficiently towards global optimal solutions. As PSO is used for its efficiency, it can search in high dimensional problem space [11]. The regular ANN model uses gradient descent to update weights whereas PSO does that more efficiently. PSO can be useful for finding the optimal solution to quantitative problems. PSO algorithm starts the process with a group of random particles. Then it searches for an optimum solution by updating generations. A series of iteration continues as PSO searches for two best values for each particle. Firstly, personal best value or p-best is considered as the best value that was achieved so far. On the other hand, the best value that is yet to be discovered is considered as g-best or global best. PSO is very good at finding global best and it gives promising results. PSO-ANN model is an optimized algorithm that hybridizes the PSO algorithm with the ANN. The PSO algorithm is a dynamic algorithm, which has a proficient and powerful ability to find accurate results around the world [10]. On the other hand, the ANN algorithm has a proficient ability to find local optimum results, yet it lacks the capability to find the global optimum result. It will be a very easy and efficient process to search for global best value by merging PSO with ANN. Considering this model, it was initialized individually at first then it was merged to see if it has done any better. Furthermore, simulation results compared to find out which showed promising results.

In research of handwritten Chinese characters recognition, using PSO-ANN got an accuracy of 96.25% and that study showed that the BP algorithm performed with lower accuracy, which was 87.8% [12]. Another study showed PSO-ANN accuracy of 82.42% for the detection of skin disease [13]. In another hybrid PSO-ANN study, sex of a person can be estimated considering bone length of the left hand and dataset consists of many groups of age people. However, that study showed the group of age from 16-19 age produced an accuracy of 96.67% and from 7-9 group of age produced an accuracy of 82.97%. On average of 80% above accuracy, these two groups of age showed better results than other groups of ages [14].

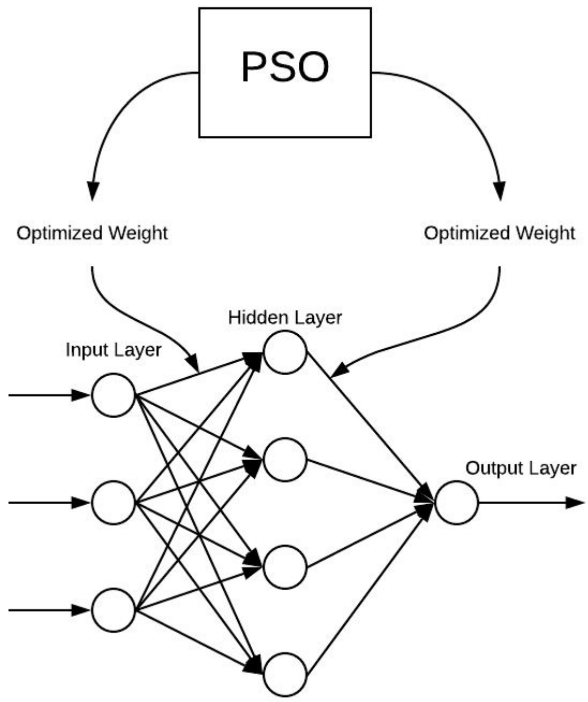

Fig 1: PSO-ANN Diagram

3. Methodology

Dataset contains categorical data, which can't be processed directly with machine learning models. It is easy to work with numerical data. Therefore, we had to encode our dataset so that machine learning models can do their tasks efficiently and correctly. One hot encoding was implemented in our dataset in order to change categorical data to integer data. After preprocessing the dataset, we trained and tested machine learning models using it.

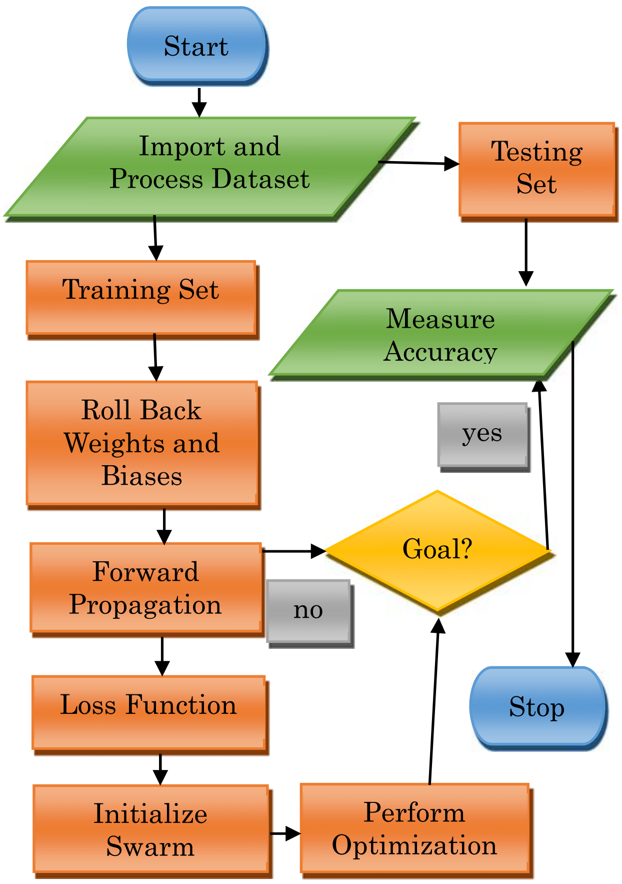

Fig 2: Flowchart of PSO-ANN

It is followed by many researchers that splitting dataset 70\%-30\% is reasonable. Large number of data is being used for to train the model and the rest is to test the model. Machine learning model needs large amount of data in order to give good accuracy score. In this research, 70%-30% ratio seemed good choice to measure overall performance of machine learning models. The ratio of the train-test split was 70%-30%. With the test set, the whole training was done. After initializing weights and biases with the rollback method, forward propagation was done which comes from the neural network. Two activation functions were used, and they are known as Sigmoid and tanh functions. After using two layers of activation functions there were 5 more hidden layers. Then the loss was calculated using loss function. Then Swarm as initialized and after that PSO was called to optimize weights. Then the updated weights and biases went through the forward propagation again. The same procedure continued until the 1000th iteration. Then the test set was used to calculate the prediction accuracy.

3.1 Pseudocode

The following pseudocode we used to important ANN-PSO.

1. Initialize the dataset
2. Randomly split into training and testing set
3. Initialize random weights and bias for each layer
4. Perform Forward Propagation on training set
5. Calculate Loss Function
6. Initialize swarm
7. Perform Optimization
8. Stop when the loss function value below the error threshold or at the number of iteration limit
9. Predict the accuracy for the testing set

3.2 Functions

Functions and methods that are used in the algorithm:
Loss Function = (Desire output – Actual output)
Roll Back = (input dimension × no. of hidden layer) + (no. of hidden layer × shape of output) + no. of hidden layer + shape of output

3.3 Pre activation Function

$$S(z) \equiv \frac{1}{1+e^{-z}} \tag{1}$$

3.4 Activation Function

$$tanh(z) \equiv \frac{e^{z}-e^{-z}}{e^{z}+e^{-z}} \tag{2}$$

4. Overview of Dataset

The dataset used in this research paper is the Road Accident and Safety data that was collected from [16] which was published by the Transport Department of the United Kingdom. Dataset’s data is of the year 2017. The dataset is related to environmental factors containing 2203 traffic accident record with 15 features. In table (1) showed description of the dataset. One of the features is a class label (Casualty Severity) and its description showed in table (2). Reference number and Accident date features were eliminated as those are not that important for processing data. So, a total of 13 features including class label are being worked on. There are no missing values.

Table 1: Dataset Description

Feature Name	Feature Description and Values
Grid Ref: Easting	Easting represents integer type values situated horizontally

Grid Ref: Northing	Easting represents integer type values situated vertically
Number of Vehicles	Vehicle's numbers in an accident are 1, 2, 3, 5, 4, 6, 7
Time (24hr)	The time of the accident occurred. Values are integer types
1st Road Class	Data type is object. Values sample 'A643', 'A61', 'A653', 'U etc.
Road Surface	1. Wet/Damp 2. Dry 3. Snow 4. Frost/Ice
Lighting Conditions	1. Daylight: Street lights present 2. Darkness: Street lights present and lit 3. Darkness: No street lighting 4. Darkness: Street lighting unknown 5. Darkness: Street lights present but unlit 6. Darkness: Street lights present and lit and lit
Weather Conditions	1. Other 2. Fine without high winds 3. Raining without high winds 4. Fine with high winds 5. Fog or mist (if hazard) 6. Raining with high winds 7. Snowing with high winds 8. Snowing without high winds
Type of Vehicle	1. Car 2. Pedal cycle 3. Motorcycle 12Motorcycle over 500cccc to Motorcycle over 500cc00cc 4. Motorcycle over 500cc0cc and under 5. Taxi/Private hire car 6. Car0 7. Pedal cycle pedal cycle 8. Motorcycle Motorcycle over 500cc0cc to 12Motorcycle over 500cccc 9. Pedal cyclecar 10. Motorcycle Motorcycle over 500cc0cc and underPedal cycle 11. Motorcycle Motorcycle over 500cc0cc and under0 12. Motorcycle over 500cc 13. Car7 14. Pedal cycle0 15. Taxi/Private hire car 16. Motorcycle Motorcycle over 500cc0cc and underMotorcycle Motorcycle over 500cc0cc and under
Casualty Class	1. Pedestrian 2. Driver or rider 3. Vehicle or pillion passenger
Casualty Severity	1. Serious 2. Slight 3. Fatal
Sex of Casualty	1. Female 2. Male
Age of Casualty	Unique Ages sample 61, 36, 32, 30, 1,…..

Table 2: Class Level Description

Casualty Severity Level	Code	Number of Instances
Fatal	0	15
Serious	1	309
Slight	2	1879

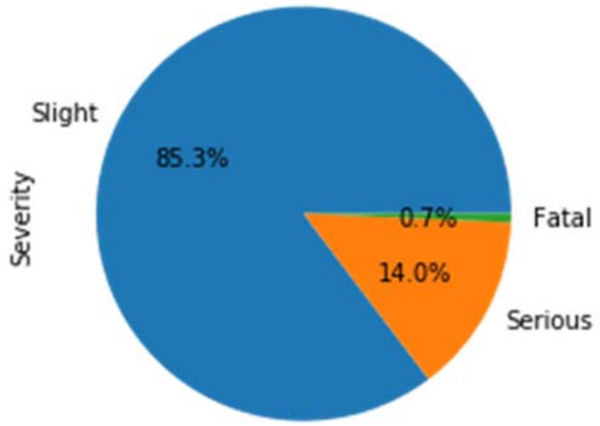

Fig 3: Class label is shown in the pie chart with a percentage value

According to figure (fig. 3) the class level has three types of data. There are slight, fatal and serious. In the dataset casualty severities, slight data is huge than fatal and serious data. The above pie chart shows that percentages.

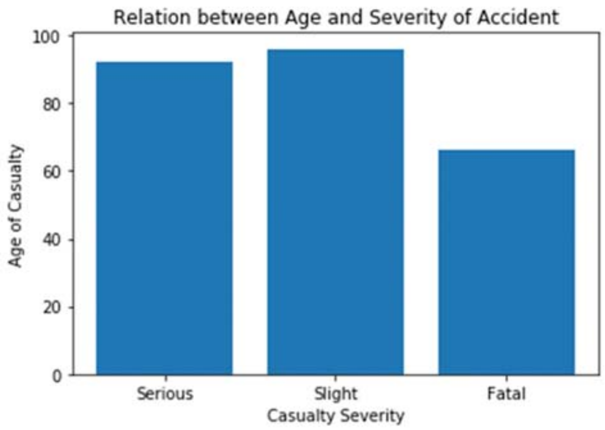

Fig 4: Bar chart of the relation between Age and Severity of accident

According to figure (fig. 4) age of under 80 people had fatal injuries. The severity level slightly occurred to most of all aged people. From the above analysis, it can be said that the group of people aging above 60 has a higher risk to be seriously injured in a traffic accident.

5. Result Analysis

In this section, the hybridized neural network and other model's performance results like accuracy, precision, recall, and f1-score are being analyzed. For every model, test accuracy is shown in percentage. In table (3) shows proposed PSO-ANN comparison by many classification methods, which are random forest, naïve Bayes, K nearest neighbor, and nearest centroid. That table shows PSO-ANN better accuracy compared to the other methods. In table (4) shows precision, recall and f1 score of every classification approach.

Table 3: Accuracy Table of different models

Name of Algorithms	Accuracy
PSO-ANN	85.06%
Random Forest	85.04%
Naïve Bayes	84%
K Nearest Neighbor	75.18%
Nearest Centroid	55%

Table 4: Table of Precision, Recall, and F1-Score

Name of Algorithms	Precision	Recall	F1 Score
PSO-ANN	0.82	0.81	0.83
Random Forest	0.82	0.85	0.81
Naïve Bayes	0.77	0.84	0.79
K Nearest Neighbor	0.76	0.75	0.75
Nearest Centroid	0.81	0.55	0.63

5.1 Performance Evaluation

We found that the best accuracy was obtained by the PSO- ANN which was 85.06%. The lowest accuracy result was achieved by the nearest centroid which was 55%. Random forest gave 85.04% accuracy. The result difference between PSO-ANN and the random forest is not huge. Naïve Bayes showed an accuracy of 84%, and K Nearest Neighbor showed 75.18% accuracy. Hybridize PSO-ANN showed promising results all over compared to other models. PSO- ANN can be considered as more reliable and accurate to give severity prediction.

In the case of precision, recall, and f1-score, the highest precision score is 0.82 which is obtained by PSO-ANN and Random forest, highest recall 0.85 obtained by Random Forest, highest f1-score 0.83 obtained by ANN-PSO. F1 score considers false positives and false negatives and it is calculated weight average of precision and recall. F1 score is more convenient than accuracy score in terms of uneven class distribution. When the cost of false positive and false negative is very different then f1 score gives much accurate result otherwise accuracy score gives accurate result of a model. If the f1- score is higher it indicates the performance of that model is better.

6. Conclusion

Predicting road accident timely can save lives and help the economy of a country. It is a global problem that needs to be reduced. The increasing number of populations is a barrier to the solution. There is another solution, the damage can be reduced along with trying to reduce accidents. To reduce damage, providing help and sending medication on time can play a huge part. To do that, the detection of the accident is needed as early as possible. In this study, the proposed model PCA-ANN provided better prediction than Naïve Bayes, Random Forest, K Nearest Neighbor, and Nearest Centroid. Different traffic scenarios can detect accidents. Road accidents should not be a barrier to the development of a country. To prevent road accidents, mass awareness is needed. But if the damage can be reduced along with reducing accidents, it will be beneficial for the economy globally and beneficial to the whole humankind.

In the future, it can be tested how the method performs with real-time data. Finding the nearest hospital and sending a notification automatically can be another step, which will send the information of the accident to the nearest hospital, and the hospital can send help immediately to reduce damage or even save a life.

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