Abstract

Road accidents amount to a significant loss of life in Lebanon. Hence an insight on the contributing factors of fatal accidents is of paramount importance. In this paper, Ensemble machine learning structured from Support Vector Machine and bagging of Decision Trees was applied to road accident data to analyze road accidents lethality on Lebanese roads. A sensitivity analysis was also carried to examine the influence of multiple factors on fatality occurrence in an accident. The model was constructed, trained, tested, and validated using 8,482 accident samples. Accident type, severity, and location were found to have the strongest impact on accident casualty.

Keywords: Fatal Accidents, Data Mining, Machine Learning.

1. Introduction

Statistics reveal that every 3 minutes a child is killed on roads, and more than 80% of road fatalities fall in low and middle income countries [1]. According to the latest WHO report published in 2017, road traffic accidents deaths in Lebanon reached 1,129 [2].

Since road safety development had not earned a high priority in Lebanon, and since most analysis done to evaluate road accidents situation are typically descriptive, we were interested in taking a new precautionary approach of analyzing accidents data collected using the Lebanese Road Accident Platform (LRAP) [25].

Feature based artificial intelligent models present a nontraditional alternative to investigating the occurrence of road accidents casualty. By predicting the fatality occurrence in an accident and the combination of variables causing it, we could use this information to better understand accidents fatality causality as a first step toward a national strategy to decrease the number of lives lost yearly in Lebanon.

The main aim is to achieve greater awareness of the conditions affecting road traffic accidents. By knowing the major factors of lethal accidents, accidents prevention authorities can adapt their behaviors and policies to improve road safety.

The contribution of this work is tow-folds: (i) develop a machine learning based intelligent model that could accurately classify the fatality occurrence of an accident, and (ii) investigate the relationship of lethal accidents with a set of input feature variables.

Using the proposed model, the ranking of the input feature variables based on their contribution and strength of relationship to the fatality occurrence were identified. Accurate results of such data analysis could provide crucial information for the road accident prevention policy.

2. Literature Review

Previous research in the Middle East region has used logistic regression to estimate the influence of accident factors on accident severity in Saudi Arabia [4]. The author’s model found that odds of fatal accidents in non-intersection location to be higher than on an intersection. He also linked accident causes such as "speed", "run red light", "follow too close", "wrong way" and "failure to yield" to impose fatal accidents using the regression model. However, regression models are subjected to the limitation in the assumption of certain forms of linear/nonlinear relationships between the exploratory variables and the variable at study.

Research conducted in Dubai focuses on applying association rules mining algorithms for traffic accidents [5]. The authors explore the link between recorded accidents’ factors to accident severity in Dubai city. Their findings conclude that death accidents occurred mostly on Tuesdays, Thursdays and Fridays in December where accidents main cause was lack of respect for road users.

In Iran, data mining algorithms such as logistic regression and Classification And Regression Trees (CART) were used to investigate the influence of human factors on road accidents severity [6]. "Driver’s license", "seat belt usage", "sex" and "age" showed to have an effect on accidents severity in Iran.

A number of studies in Turkey also have attempted to develop severity models including a study to predict the severity of motor vehicle accident injuries in Adana city using machine learning methods [7]. Another study used artificial neural network model to estimate the number of accidents, fatalities, and injuries in Ankara city, Turkey [8].

3. Source Data Preprocessing

The experiments were carried out using Weka environment. Weka is an open source toolkit that provides a set of machine
learning and pre-processing algorithms [9].

Input accidents data was procured from the Lebanese Road Accidents Platform (LARP) built in the scope of a national project to study accidents in Lebanon [25]. The platform produces the database of the accidents occurring in Lebanon by crowdsourcing reported accident statistics on social media from three credible governmental sources. The data records used consisted of 8,482 data records spanning from February 2015 until February 2019. The database contains the following information about road accidents all over Lebanon: location, time, type of accident, the number of injuries, and the number of lethal victims [24]. Additional information such as roads’ characteristics were extracted from the Lebanese roads’ shapefile available at Open Street Map.

To account for the spatial feature of the data, K-means clustering is applied to all crash events and the cluster ID is passed as an input variable to the model. Hence, after refining the data and parsing the needed information, nine input variables were selected in this study and the output variable is the fatality occurrence. Table 1 demonstrates the input and output features selected with their correspondent ranges.

| Table 1: Input and Output Variables |
|-------------------------------------|
| **Input Variables**                 |
| Month                               | 1-12 |
| Day                                 | 1-31 |
| Day of the Week                     | Monday-Sunday |
| Hour of Accident                    | 0-23 |
| AM/PM                               | am, pm |
| Accident type                       | Vehicle-Vehicle, Vehicle-Truck, Vehicle-Pedestrian, Vehicle-Bike, Vehicle-Barrier, Truck-Truck, Truck-Bike, Truck-Barrier, Bike-Bike, Bike-Barrier, Others |
| Severity Level                      | No-Apparent-Injury, Minor-Injury, Serious-Injury |
| Road Type                           | Motorway, Primary, Secondary, Tertiary, Trunk, Unclassified |
| Spatial Cluster Id                  | 1-10 |
| **Output Variables**                |
| Fatality occurrence                | Lethal, Not-Lethal |

The data was divided into three sets as follows, 20% as test data, the remaining 80% is split into training and validation sets. The training dataset is the set that the software uses to learn the machine learning algorithm selected. The validation data set is used to give an estimate of model skill while tuning model’s hyper-parameters. Validation is done through the 10-folds cross validation technique.

The advantage of this method is that all observations are used for both training and validation, and each observation is used for validation exactly once. The test dataset is data unseen by the model to assess the final performance of a fully developed classifier.

The distribution of the two fatality classes showed to be not equally represented in the dataset acquired with 95% of the samples labeled as Not-Lethal accidents and only 5% as Lethal. The imbalanced categories in classification problems cause negative effect on the classification performance. Imbalance on the order of 100 to 1 is prevalent in fraud detection [11]. Dealing with imbalanced data can be approached in two ways: (i) either by using cost sensitive learning algorithms or (ii) by re-sampling the dataset which is more popular due to many factors one of them is that not all learning algorithms have cost sensitive implementations. [12].

Re-sampling the data is done either by under-sampling the majority class or by oversampling the minority class. Under-sampling produces a random subset of the majority class to train the classifier. The main drawback of this method is the potential loss of information. Oversampling can simply be done by producing random copies of the minority class. The main disadvantage of oversampling by replacement is that by making exact replicas of existing instances, it increases the chances of over-fitting.

Chawla has proposed Synthetic Minority Over-Sampling Technique (SMOTE) [13], an over-sampling approach in which the minority class is over-sampled by creating synthetic examples rather than by replacement. These synthetic examples are introduced along the line segments joining any or all the K-minority class nearest neighbors. Depending on the amount of over-sampling required, neighbors from the K-nearest neighbors are randomly chosen.

While under-sampling forms a potential of losing information, and over-sampling increases the sample size worsening the computational power needed, a hybrid technique is proposed in [13] that combines under-sampling and synthetic oversampling. This technique proved to achieve better classifier performance in our study and hence was adopted.

The key factor when using sampling technique is to produce a better distributed dataset that is as much representative sample as possible. For this study, based on testing, we employed re-sampling on the data level by oversampling the minority class 100% using SMOTE with 5 nearest neighbors and under-sampling the majority class afterward so that the new distribution would have 83% majority class and 17% minority class. This split would decrease the imbalance effect while preserving the real distribution of data. The sampling technique is a pre-processing phase that should be applied to the training set only without altering the validation and test set. In the Weka environment, we used nested filtered classifier to ensure that the oversampling with SMOTE filter is applied first before the “Spread-Sub-Sample” filter that does the random under-sampling.

4. Model Development and Evaluation Metrics

4.1. Model Development

The model is built based on hybrid ensemble technique. The motivation of using ensemble on classifiers can be of an analogy to consulting multiple doctors before taking final decision on critical cases.
Classifier Ensemble is a combination of different individual classifiers in order to perform the classification task jointly. If those individual classifiers are diverse i.e. disagree with each other, then their random errors will cancel each other and will help to output correct decisions. Multiple research showed the effect of ensemble methods on the improvement of performance and the reduction of over-fitting issue [17].

In homogeneous ensemble, all classifiers are of same type, where as in heterogeneous ensemble, the classifiers are different. Some ensemble techniques such as bagging and boosting use homogeneous ensemble where as others such as voting and stacking use heterogeneous ensemble.

Bagging is to have multiple classifiers trained on different under-sampled subsets and allow these classifiers to vote on a final decision, rather than using just one classifier. Random Forest is an extension of bagging for decision trees. Bagging is preferred to use with unstable algorithms, where the small changes in the training set, result in large changes in the output of that system [18]. Boosting is to have a series of classifiers to train on the dataset, but gradually putting more emphasis on training examples that the previous classifiers have fail. Boosting works best if the aim is to reduce chances of under-fitting.

The use of such homogeneous ensembles may not be the best choice for problems where the ideal base classifier is unclear. Authors in [18] argues that using heterogeneous produces better performance.

Voting as a heterogeneous ensemble works by creating two or more sub-models. Each sub-model makes predictions which are combined in some way, such as by taking the mean or the mode of the predictions, allowing each sub-model to vote on what the outcome should be. Stacking is a simple extension to Voting ensembles; stacking allows to specify another model to learn how to best combine the predictions from the sub-models. Because a meta model is used to best combine the predictions of sub-models, this technique is sometimes called blending, as in blending predictions together. Stacking and Voting reduce the risk of over-fitting and improve predictions.

In this paper, we use hybrid combination of heterogeneous ensemble with homogeneous ensemble through ensemble of Support Vector Machine (SVM) with bagging of J48 decision trees. Bagging stable learners is less advantageous since the ensemble will not help improve generalization performance. Hence, Bagging of J48 decision tree is adopted for the fact that decision trees are highly based on random node splitting. Voting is performed using averaging probabilities. Each base learner produces a classification with a certain probability then these probabilities are averaged, and a new classification is outputted based on the new averaged probability.

4.2. Evaluation metrics

Measures of the quality of classification are built from a confusion matrix which records correctly and incorrectly recognized examples for each class. The performance of machine learning algorithms is typically evaluated using predictive accuracy metric as shown in Equation 1:

\[
\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN}
\]

where \(TP\) stands for True Positive, \(TN\) True Negative, \(FP\) False Positive and \(FN\) False Negative.

An area under a receiver operating characteristic curve (also known as AUC-ROC) can also indicate a balanced classification ability between true positive rate and false positive rate. However, such metrics are not appropriate in our case where the data is imbalanced since accuracy, does not distinguish between the number of correct labels of different classes. For example, for data with 95% negative instances and 5% positive instances, classifying all instances as negative instances would produce an accuracy of 95%. When the cost of correctly detecting the minority class is evidently higher that the cost of detecting the majority class, accuracy will not be a good evaluation measure. Also, according to [14], AUC-ROC discriminates well between good and bad models, but not between good models.

Other metrics are suggested when we are interested in effective detection of one class more than the other such as Precision defined in Equation 2, Recall defined in Equation 3, and F-measure defined in Equation 4.

\[
\text{Precision} = \frac{TP}{TP + FP} \quad (2)
\]
\[
\text{Recall} = \frac{TP}{TP + FN} \quad (3)
\]
\[
F\text{-measure} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \quad (4)
\]

Other metrics such as Cohen’s Kappa Statistic defined in Equation 5, can be used to evaluate classifiers with imbalanced data. Kappa is a measure of how closely the instances classified by the machine learning classifier matched the data labeled as ground truth, controlling for the accuracy of a random classifier as measured by the expected accuracy. It basically states how much your classifier is performing better than a classifier that is simply guessing at random according to the frequency of each class. Cohen’s Kappa ranges from -1 to 1. Values less or
equal to zero indicate that your classifier is guessing at random and not intelligent.

Landis and Koch evaluated the performance of a classifier from the value of Kappa statistic according to their scheme in [16]. They consider values of $0 - 0.20$ as "slight", $0.21 - 0.40$ as "fair", $0.41 - 0.60$ as "moderate", $0.61 - 0.80$ as "substantial", and $0.81 - 1$ as "almost perfect".

$$\text{Kappa} = 1 - \frac{1 - po}{1 + pe}$$  \hspace{1cm} (5)

where $po$ is the observed agreement and $pe$ is the expected agreement.

For the scope of this work and to fulfill the requirement of effective evaluation of the lethal class, $F$-measure, $AUC-PR$, and Cohen’s Kappa Statistic are used as evaluation matrices for our classifier.

5. Results

5.1. Classifier Selection

Finding the best performing classifier is an iterative process. We started by building models with single learning algorithms and tuning their hyper-parameters. The best two performances were achieved by SMO, followed by Random Fores. Table 2 shows the models performance measures for the various classifiers for the lethal class.

### Table 2: Performance metrics of single learning classifiers.

| Classifier      | F-measure | AUC-PR | Kappa   |
|-----------------|-----------|--------|---------|
| SMO             | 0.493     | 0.276  | 0.4678  |
| RandomForest    | 0.453     | 0.376  | 0.4258  |
| ANN             | 0.385     | 0.291  | 0.3462  |
| Logistic Regression | 0.455  | 0.361  | 0.4309  |
| Naive Bayes     | 0.313     | 0.337  | 0.294   |

Given the out-performance of ensemble methods in the literature, we tried various ensemble method of the best two classifiers to find that bagging of J48 decision trees 100 times outperforms random forest of 100 trees. This might be because random forests method only selects a subset of features at random out of the total and the best split feature from the subset is used to split each node in a tree, unlike in bagging where all features are considered for splitting a node. Best performance was achieved by using a hybrid ensemble technique: Vote SMO with Bagging J48 as shown in Table 3.

### Table 3: Performance metrics of selected classifiers using ensemble method.

| Classifier             | F-measure | AUC-PR | Kappa   |
|------------------------|-----------|--------|---------|
| Bagging J48            | 0.464     | 0.382  | 0.4365  |
| Vote SMO with Bagging J48 | 0.493 | 0.402  | 0.4678  |

Table 4 shows the validation set results and the unseen test set results for the lethal class using the Vote SMO with Bagging J48 classifier.

### Table 4: Performance metrics for the "Vote SMO with Bagging J48" classifier over validation and test datasets.

|                    | Validation Set | Unseen Test Set |
|--------------------|----------------|-----------------|
| F-measure          | 0.493          | 0.435           |
| Cohen’s Kappa      | 0.4678         | 0.4067          |

A $Kappa$ statistic of 0.4067 shows that the model is considered as moderate classifier. An $AUC-PR$ value of 0.368 is considered good for our data that has highly skewed class distribution since there are areas of the Precision-Recall curve that are un-achievable [19].

Comparing the Precision-Recall curve of our model that has imbalanced data of ratio 1:19 in Figure 1 with the reference Precision-Recall curve of imbalanced data of ration 1:10, we can conclude that our model has good early retrieval that is considered as a good model.

5.2. Sensitivity Analysis

To examine the impact of each input features and the information gained from it to predict the output variable, a sensitivity analysis was performed by applying, given the categorical nature of the attributes, Chi $-squared$’s correlation evaluation of each attribute to the output variable in the context of the model. The input features are ranked and analyzed on their importance in the prediction of the fatality occurrence. The Chi $-squared$ values are compared to a critical Chi $-squared$ value calculated assuming independent variables. A large value above the critical value implies that they are not correlated.

The ranking of the input variables based on their contribution and strength of relationship to the fatality occurrence were identified by analyzing the sensitivities of the input variables to the output variable. Results showed that seven attributes out of the nine are correlated to the output variable. Figure 2 shows the attributes ranked in increasing order from the most correlated to the least with their corresponding chi square value.

Based on the chi square correlation test results shown in Figure 2, the variables associated with the increase likelihood of fatality in accidents are ordered as follows:

1. Accident type (parties-involved)
2. Severity Level
3. Spatial Cluster id
4. Hour of Accident
5. Day of the week
6. Road Type
7. AM/PM

Whereas, the Month and the Day of accident variables appear to be independent from the fatality occurrence. In agreement with [21] that argues that the type of vehicle has the most impact on crash severity, our model found that the type of the vehicles involved in crashes is the most important factor that affects crash fatality occurrence.
6. Discussion

A deeper dissection of the results in Figure 2 discusses the impact of each variables category on the fatality occurrence.

For accident type, it was found that the Vehicle-Pedestrian type is the most influencing variable on the fatality occurrence. This is logical as pedestrians are volatile. In Lebanon, pedestrians lack the proper awareness of using walking sidelines and pedestrian bridges. They also attempt to cross two-lane highways that have neither stop signs nor traffic signals. Drivers nevertheless violate pedestrians right on the road by not slowing down on walking sidelines or when seeing a pedestrians crossing the road. According to the Committee of Land Transport in the Global Safety Organization, human factor is the main reason for traffic accidents [20]. Among the human factors, pedestrians ignoring traffic signals and sidewalks and drivers ignoring the right of pedestrians whilst on the road.

Furthermore, accidents involving a truck hitting a motorcycle attain the second most influencing accidents type on fatality occurrence. Given the dramatic difference in size between the two vehicles, the potential for casualty is certain since it is easy for a motorcyclist to be caught in a blind spot of a truck on the road. Motorcyclists in Lebanon do not follow the law that states that the motorcyclist should wear a helmet, drive on the right most lane, do not accompany more than one person with him on the motorcycle, and do not escort along children aging less than 10 years. Such violations enhances the damage if a truck-motorcycle occurs and leads to fatality.

As for the Severity Level variable, the crashes with serious severity level are highly correlated to the death episode. With the increase in severity resulting from a crash, the probability of death occurrence is anticipated. Linking the death occurrence with the distribution of emergency support centers, we can estimate that the response time is relatively high which induces the death of the injured crash victims. In further study, we intend to analyze the response time and distribution of emergency support and their effect on the lethality of vehicle crashes according to the golden hour standard.

Digging in the spatial distribution of lethal accidents, major cluster is obtained in Al-Maten and Keserwan districts. Given that those areas have the highest GDP in Lebanon, the families tend to buy cars for their children at very young ages. With the increase in number of youth driving, the lethal accidents increase. Some families even buy cars for adolescence who still do not meet the age appropriate for getting a driving licence. Such cultural attitude increases the fatality occurrence. On the other hand, Keserwan and Al-Maten areas retain the most important highways in the country making such areas in danger from speedy careless drivers. Nevertheless, these areas are densely populated with people migrating back and fourth to Beirut daily creating heavy traffic on highways and violation of traffic laws by using the sidelines as extra lanes and hence increasing the chances of hitting a parked vehicle or a road barrier.

Time of the day more specifically 3 am was highly correlated with fatality occurrence. This could be possibly explained by the diminish in clear sight which decreases the driver’s ability to bypass collision. Other human related factors include sleepiness symptoms that drivers experience at such hours and the high probability of colliding with a drunk driver. Sleepy or fatigue driver resulted in higher severity crashes which foster death [22]. The crashes occurring due to sleepy drivers might be linked to the old fleet of cars that Lebanon has and its lack of alerting systems which the new cars manifest. It is up to the government to solve such issues whoever, based on our study we recommend placing radar detectors and performing alcohol tests to drivers at such late hours.

Unsurprising Friday and Sunday were the two most influencing days of the week on the occurrence of lethal accidents. These two days correspond to the beginning and ending of the weekend respectively where weekly migration from and to Beirut occur. The excess volume of cars on motorways make drivers impatient leading to careless driving and hence severe accidents. Also, on the weekend, people in Lebanon tend to go out to the mountains and drive speedily in unfamiliar roads which increases the chances of hitting a parked vehicle or a road barrier.

Furthermore, Road type and more precisely motorways are correlated with fatal accidents in Lebanon. Reasons might be drawn back to the roads infrastructure, speed variation, and lighting conditions. Geometric design shortage on existing roads would lead to a potential severe accident, such as an accident happens at the sharp curves, layered pavement conditions, and
slippery pavement surface[23]. Also, motorways in Lebanon have three lanes which converge to two lanes very often leading to a sudden decrease in speed which in return adds the risk of fatal accidents. Major motorways in Lebanon also lack proper street lighting in night-time proliferating the risk of severe collision.

The sensitivity analysis was made to analyze key factors associated with vehicle accidents and to be able to identify which factors have the most influence on the fatality occurrence during the vehicle collision. The ability of the model to uncover which variables played the most significant role in fatality occurrence would be able to aid investigators in finding a solution to reduce the fatality rate of road accidents.

7. Conclusion

The costs of fatalities and injuries due to traffic accidents have a great impact on society. The main intent of this study was to provide a demonstration of a model that can be used to assess the most important factors contributing to the fatality occurrence of traffic accidents in Lebanon.

The increase in accidents data made it harder to analyze and extract useful information from them. Data mining techniques came as the solution as it provides much deeper analysis and extracts valuable knowledge embedded in the data thus resulting in interesting findings. Data mining involves an integration of techniques from multiple disciplines such as database technology, statistics, machine learning, and spatial data analysis.

In our study, we employed an ensemble data mining classification technique that combines SVM and bagging of decision trees using 8,482 accident samples. The model was validated using cross validation and tested on unseen test set. The model integrates the spatial information into the model using K-means clustering.

Given the nature of accidents, there are multiple aspects that contribute to the fatality occurrence. Variables not used in this study could affect the results of the model. Also, with more future accidents data fetched, the model will improve to estimate better results and discover links between variable not uncovered yet. Future research question remains, how sensitive the classification is to accident parameters.

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