Text-clustering based deep neural network for prediction of occupational accident risk: A case study

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***Abstract*—Predicting occupational accident risk using both structured and unstructured (text) data is broadly an unexplored area of research. Unstructured texts, i.e., incident narratives often remain unutilized or under-utilized. Besides the explicit attributes present in the dataset, there exist a large number of hidden attributes in different forms, which are hardly explored by the traditional machine learning algorithms. Therefore, we propose a methodology that utilizes both text-based clustering, namely Expectation Maximization (EM) algorithm for unstructured text analysis and deep neural network (DNN) for prediction of accident risk using the accident data collected from a steel plant in India. EM-based DNN shows the maximum accuracy equal to 83.59% in the prediction of risk while compared to other algorithms, namely single DNN, support vector machine, and random forest. In addition, it is also explored that the use of text data enhances the prediction accuracy in accident analysis.**

Index Terms—Occupational accident risk; Prediction; Text-based EM clustering; DNN.

I. Introduction

The occupational accident is a serious concern for every industry. According to the statistics provided by the International Labour Organization (ILO), about 2.3 million workers succumb to death annually due to occupational accidents and diseases in the whole world, which include 3.6 lakh fatal accidents approximately [1]. Nearly 337 million occupational accidents are reported each year. About 4% of the annual gross domestic product (GDP) is spent due to occupational accidents. Relating to this fact, ILO remarks: *"Fatalities are not fated; accident do not just happen; illness is not random; they are caused"*. Behind each of the incidents, there is a chain of multiple factors interacting with each other in a specific pattern. If the pattern is identified, the incident outcomes can be predicted. Once the outcomes are predicted, the occurrence of incidents can be minimized, which results in a decrease in occupational accident risk. A predictive model, in these cases, is playing a key role by identifying the inherent patterns and subsequently predicting the risk of an occupational accident. The data-driven predictive model is nowadays widely used in diverse application areas from conventional data analysis to image processing [2] to decision support system [3] to advanced hyper-spectral data analyses [4]–[8] than qualitative questionnaire-based decision-making analyses [9]–[11] or traditional statistical-based analysis [12], [13]. According to the study by Ciarapica and Giacchetta [14], industries are more concerned with occupational risk analysis and safety predictive model building to reduce the occurrence of accidents. Therefore, the use of the predictive model is very important in accident risk prediction.

In practice, accident data are collected and stored in different forms, such as categorical, numerical, unstructured text or narratives etc. either before or after the occurrence of accidents [15], [16]. Of them, handling of texts related to accidents is a very difficult task for analysis. Usually, once an incident is taken place, safety professionals usually narrate the incident event in their own language and log them into the electronic database. Therefore, the exactness of the incident mostly depends on the experience and writing quality of the personnel. It is often found out that the incident narratives remain underutilized or sometimes unutilized since the proper utilization of unstructured text data for information retrieval demands a huge amount of human effort. Reviewing the incident narratives during the investigation is extremely time-consuming. In addition, narratives are sometimes written in such a way that useful information can hardly be sufficiently extracted and analysed. Indeed, analysis of this type of data has been so emphasized that the accumulated descriptions through accident texts have been mostly ignored [17]. As a consequence, the situation may lead to a biased judgment. Moreover, the narratives often are written in short form, which leads to the problem of sparseness with higher dimensionality. It ultimately results in the problem of insufficient word co-occurrence and a dearth of context information [18]. Under such condition, categorization of text becomes difficult [17], [19]. In order to address the issues, text clustering approach has been used by previous researchers, which helps to cluster the unstructured text in a meaningful way. It is a potential text mining tool to extract hidden information from the text. In this text clustering, there is a number of algorithms, which can be used, such as k-means [20], [21], self-organization map-based k-means [22], [23], expectation-maximization (EM) [24], [25], hierarchical clustering [26], [27], etc., which have been used in different application areas successfully. However, in the accident analysis domain, the use of text clustering is rather limited [28], [29]. Of them, EM algorithm has been recently adopted by many researches due to its several notable advantages, which include the robustness to noise data, capability of handling high dimensional data and in particular, faster convergence to an optimal solution, whereas a good initialization is given [30].

In the occupational accident analysis, as the data are collected and stored in a broader spectrum, traditional data analysis techniques, for example, statistical analyses are often found to be less efficient. Machine learning (ML) technique, in this case, is well-accepted, as opposed to its traditional counterpart. The traditional ML algorithms, such as artificial neural network (ANN) [22], support vector machine (SVM) [22], and decision tree algorithms like classification and regression tree analysis (CART), C5.0, random forest (RF) have been used in classification task [31]–[33]. The more can the algorithms extract the patterns of the factors from data, the more will be the classification accuracy. Some earlier studies even used parameter optimization techniques for improved classification accuracies [33], [34] or pattern extraction for better interpretation of accident data using association rule mining [35], rough set theory [33]. Sometimes, Bayesian Network followed by sensitivity analyses have been carried out to evaluate the importance of the factors towards incident outcomes [33]. But there always exists a number of hidden attributes in different form of data, which can hardly be extracted by conventional ML techniques. The deep learning method here comes into practice, which can extract the hidden attributes and consequently explore the patterns from the texts, consequently increase the classification accuracy [36]. In fact, deep neural network (DNN) shows superior performance while dealing with natural language processing (NLP) [37]. However, in accident analysis, the application of DNN is very limited. Zheng et al. [38] used Pythagorean-type fuzzy DNN model for the early detection system of industrial accidents in China. They suggested that DNN was capable to proactively prevent the accident. In 2018, in the domain of computer vision and pattern recognition on human behavior, Ding et al. [39] attempted to recognize workers' unsafe actions using a hybrid deep learning model integrating a convolution neural network (CNN) and long short-term memory (LSTM). The results of their experiments revealed that the proposed approach was capable of detecting safe/unsafe actions of workers on site. One recent study by Fang et al. [40] addressed the issues of fall from heights in a construction site in China. They developed an automated computer vision-based method using two CNN models to determine whether the workers wearing the safety harness during their work at heights from the image data. The performance of their models reveals more than 90% prediction/classification accuracy. Therefore, it can be realized that the use of DNN in prediction task holds more potential, particularly, in accident analysis.

A. Research issues

Based on the literature presented above (though not exhaustive in nature due to the limitation of space), some issues are identified in the occupational accident research, which are summarized below.

1) Use of both text and categorical data analysis is limited.

2) Extraction of hidden factors and patterns from data is not reported till date.

B. Contributions of the study

Based on the issues identified, and being motivated by the utility of EM-based text-clustering and DNN, the present study, to the best of authors' knowledge, endeavors to contribute in the domain of accident analysis in the following ways:

1) Both unstructured text and categorical data have been used.

2) EM-based text clustering has been used to extract the information from the accident narratives/texts.

3) In order to extract hidden attributes and patterns for prediction of accident risk, DNN has been employed.

4) To validate the proposed model, a case study of an integrated steel plant has been carried out.

The remainder of the paper is structured as follows: In **Section II**, methods used in this study have been presented briefly. In **Section III**, a case study is provided with data collection, data description, and data preprocessing steps. Results and discussions of the analyses are presented in **Section IV**, and finally, in **Section V**, the conclusion is presented with the scope for future works.

II. METHODOLOGY

Once the data are collected from the electronic database of the safety management system of an integrated steel plant, the pre-processing tasks are performed, such as removal of inconsistency, duplicate entry, and missing data. One new attribute called 'Clusters' is generated from the unstructured injury narratives using EM-based text clustering approach. Therefore, all the attributes in accident data set are transformed into categorical only. This is finally used for building the DNN model. In this study, it is checked and compared whether the EM-based DNN classifier performs better than that of individual DNN or not in the prediction of occupational injury risk without text feature. In addition, SVM and RF algorithms are also used without the text information. The entire methodology from the data collection to final prediction is depicted in Fig. 1. The methods like the EM-based text clustering, and DNN used in this study are briefly discussed in the following section.

A. EM-based text clustering

EM is the extension of the k-means clustering technique. Its working principle is based on a generative process used to cluster the texts. The algorithm works holding the initial assumption that the words within a particular document are generated by a mixture of the probability distribution. The steps of this algorithm are explained in Fig. 2. For detailed understanding of EM algorithm, interested readers are referred to [41], [42]. In order to determine the optimal number of clusters, 'Silhouette coefficient' has been used [22] in this study.

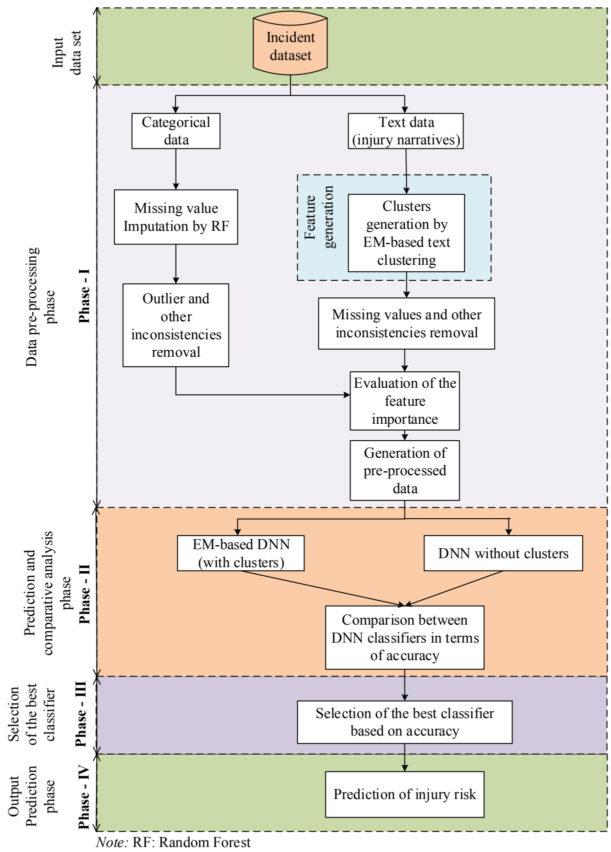

Fig. 1: Proposed research methodological flowchart.

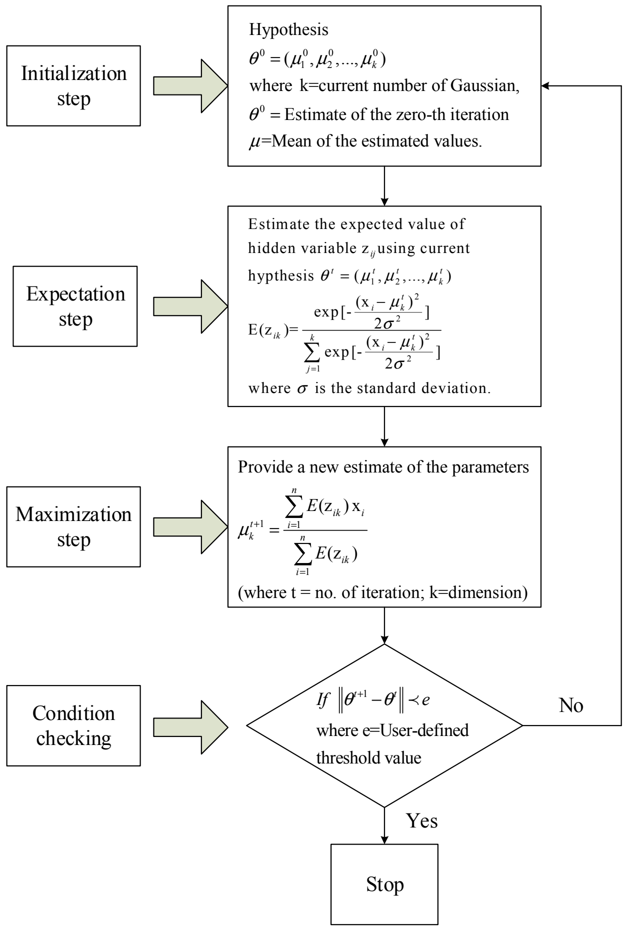

Fig. 2: Flowchart showing the steps of the EM algorithm.

B. Deep neural network (DNN)

A typical DNN structure comprises a stacked autoencoder (SAE) with an autoencoder and a SoftMax classifier. An autoencoder (AE) is a feed-forward ANN comprising one input layer, one hidden layer, and one output layer. Usually, it is trained to copy its input to its output so that the errors become minimum. Therefore, the dimension of the input must be the same as that of output. A stacked autoencoder is a neural network consisting of multiple layers of sparse autoencoders in which the outputs of each layer is used as the inputs of the successive layer. The encoder sections of the desired number of trained AEs are cascaded to construct a stacked autoencoder (sAE) network. For more details, interested readers are requested to refer to [43].

III. CASE STUDY

The incident data consists of 3488 occupational accident records from 2010 to 2013. The data, its attributes, and the pre-processing techniques are described in the following sections.

A. Data collection and data description

Once the data are collected, they are preprocessed and validated by domain experts. The dataset consists of thirteen features (12 categorical, and one free unstructured texts, which is transformed into clusters) of which the feature "Injury risk" is considered as the response variable (refer to Table I).

B. Data pre-processing

Pre-processing of data, being an important task of data mining, usually demands more than 60% of the total effort in the entire modeling process. Apart from the removal of inconsistencies, outliers, and missing data, new feature or attribute has been generated in this pre-processing step, which is explained in the following section.

IV. RESULTS AND DISCUSSIONS

A. Feature generation from unstructured text

In this feature generation, the accident narratives are transformed into meaningful clusters using the EM algorithm. The new feature (called as "Clusters") generated from the transformation has eight optimal number of classes, as determined by 'Silhouette coefficient' (refer to Fig. 3).

B. Evaluation of feature importance using Chi-square approach

Using Chi-square approach, the importance of each of the features is evaluated (refer to Fig. 4). The features, namely 'Incident types', 'Clusters', 'Primary causes', and 'Incident outcomes' are found to be the important predictors of occupational risk; whereas the features like 'Employee types', 'Working conditions', 'Day of incident', and 'Month of incident' are found to be less important.

TABLE I: Features with corresponding categories used in the study.

SN	Attributes	Category
1	Day of incident (DOI)	7
2	Month of incident (MOI)	12
3	Divisions (Div.)	13
4	Incident outcomes (IO)	3
5	Primary events/causes (PC)	10
6	Working conditions (WC)	3
7	Machine conditions (MC)	3
8	Observation types (OT)	4
9	Employee types (ET)	2
10	Incident types (IT)	2
11	Injury risk	3
12	Standard operating procedures (SOPs)	6
13	Clusters	8

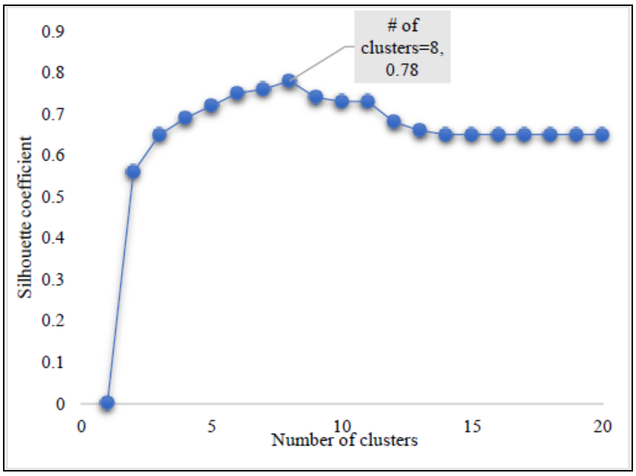

Fig. 3: Determination of the optimal number of topics using Silhouette coefficient.

C. Predictive analysis

In this section, the results of the classification task have been discussed. Apart from DNN, two more classifiers, namely SVM, and RF have also been used on the dataset. The hyper-parameters of a DNN include learning rates, activation function, number of hidden layers, and the number of neurons in each hidden layer. Using grid search technique, the suitable value for number of hidden layer, number of nodes per hidden layer, learning rate, activation function, and dropout probability are obtained as 5, (6, 5, 5, 4, and 6), 0.5, Rectified Linear Unit (ReLU) activation function, and 0.2, respectively (refer to Table II). It is noteworthy to mention that the activation function ReLU is applied on hidden layers to overcome the issue of ‘vanishing gradient of errors’. In addition, the parameter, ‘dropout probability’ is used in this study to prevent the over-fitting problem. With these suitable values mentioned in Table II, the performances of

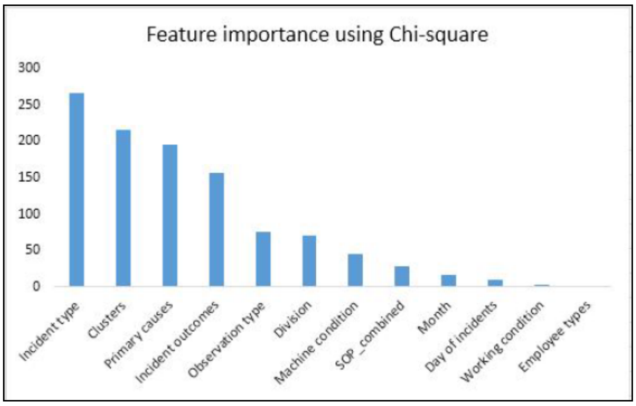

Fig. 4: Feature importance using Chi-square technique.

TABLE II: Optimal values of hyper-parameters of DNN.

Hyper-parameters	Values
Activation function (at hidden layers)	ReLU
Number of hidden layers	5
Number of nodes per hidden layers	(6, 5, 5, 4, and 6)
Dropout probability	0.2
Learning rate	0.5

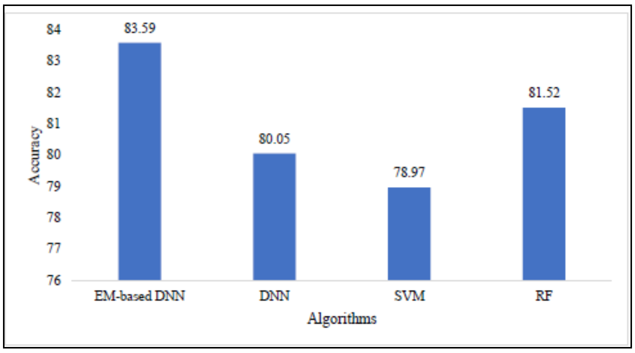

Fig. 5: Performance comparisons of the classifiers based on accuracy.

EM-based DNN (considering text) is compared with that of single DNN model (i.e., without considering text), SVM, and RF based on accuracy using 10- fold cross-validation (refer to Fig. 5). The EM-based DNN classifier produces superior accuracy as high as 83.59%.

To check the robustness of the classifiers used in this study, separate five runs were also carried out using 10-fold cross-validation. According to the steps used by Sarkar et al. [22], seeds with the different random order are utilized for training and testing. The seeds are assigned to odd numbers, e.g., 43, 45, 47, 49, and 51 for 5 individual runs. This step produces a set of cross-validation folds for each run. As a consequence, 50 accuracies are obtained for each of the models, which aids to generate box plots for each of the classifiers (refer to Fig. 6). From this figure, the maximum accuracy yielded by EM-based DNN algorithm as compared to others with the lowest degree of dispersion is observed. Hence, EM-based DNN algorithm is found to be the robust model. Based on these results in terms of both accuracy and robustness, the EM-based DNN algorithm is considered to be the best model among the four classifiers.

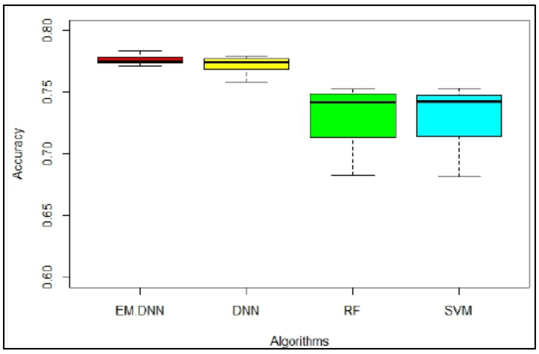

Fig. 6: Box plot analysis for robustness checking of different classifiers.

V. CONCLUSIONS

In the current study, predictive models based on a machine learning approach, namely EM-based DNN, normal DNN, SVM, and RF have been developed for prediction of the level of an injury risk at work. EM-based DNN model has been compared with DNN, SVM, and RF classifiers, separately. The results reveal that EM-based DNN outperforms others with the highest accuracy equal to 83.59%. Moreover, the boxplot analysis also explores that the proposed model is robust. Besides the application of the classifiers, a proper sequence of data preprocessing task has been discussed. Text-based EM clustering algorithm on unstructured text has been found to be useful to extract the clusters, which has been also verified by Chi-square approach for feature importance. Using this approach, it is also explored that the attributes ‘Incident types’, ‘Primary causes’, ‘Incident outcomes’, ‘Observation types’ are also good predictors of ‘Injury risk’.

The study has also some limitations. The dataset consists of less amount of description. Moreover, the architecture design of DNN is found to be very sensitive towards the proper selection of its parameter values. As the scope of future works, genetic algorithm or particle swarm optimization techniques could be employed to find the optimal number of clusters. In addition, these optimization techniques could also be employed to enhance prediction accuracy. An interesting avenue for future researchers in this domain is the development of a decision support system (DSS). On top of that, the present study can be used also in different domains, such as mining, aviation, construction, and so forth.

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