

Design and Development of Rail Transit System Safety Competencies through Full-text Retrieval of Big Data Analysis

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ABSTRACT

The railway station is a critical aspect, and yet rail accidents occurred from the overall structure of the system. Based on the signal processing method, the report of fault tracking is analyzed by the feature extraction based on the regular expression, and text format has adopted the feature of accident name, source and destination, rail name, accident location and so on from the overall structured and unstructured big data railway accident fault information analyzing and retrieving become a challenging task. It is time to investigate the errors and improve the predictable method by utilizing the latest technology, such as Deep (DL), to analyze rail accidents and enhance safety systems from rail transit systems. By integrating the domain dictionary of a railway which integrates the segmentation of mainstream index technology to realize quick indexing after segmenting words and applies Frequency-Inverse Document Frequency (TF-IDF) algorithm to realize the full-text search. The proposed system describes the use of Full-Text Retrieval from a large amount of data which is distributed through a full-text search engine using Term of TF-IDF algorithm retrieval scheme based on distributed full text from search engine to understand complete search text. The results show that accuracy prediction for rail accidents significantly improved by utilizing features by full-text retrieval and further improves the competencies to minimize rail accident safety.

Keywords: *Big data; deep learning; rail transit system; TF-IDF; signal processing and analysis; full-text retrieval and safety competencies.*

INTRODUCTION

The transposition of the railway has become a speed, reliable, and high capacity for being associated with good transportation and passengers and they have high risk in terms of cost of assets and human lives. The railroad's involved accident submitted reports that contain both narratives and fixed entire fields that described the characteristics of the accident. Even if there is a small improvement in this railway sector will help the overall growth of the nation. Due to the gigantic size, it is a difficult task to maintain and monitor the rails promptly. The overall track results of the rail because of poor maintenance [1-3]. New technologies are applied for the railway, and efficient safety measures are led from time to time, but still, accidents occurred. Significantly the research shows for finding a text mining to contribute to the rail accident with a possible way to fix the field of accident report analyzing. The study contributes to the presentation of Deep Learning (DL) and extracting the feature of text retrieval for ensuring safety and gaining benefits by powerful algorithms. Unstructured railway accident reports are maintained by including a database of an accident report, fault tracking reports, and so on [4-5]. These text files are normally maintained by several formats. These texts are hard to discover by using the proposed algorithm of TF-IDF; the big data are decentralized distributed and full-text retrieval of a railway through deep learning method. The advanced method of text retrieval and deep learning has given the new capability of the process, and textual contents are classified automatically. The research describes the results by

 https://doi.org/10.37896/pd91.4/91493

ISSN: 0369-8963

using the advanced technology in deep learning to process the cause of accidental classified, accidental narratives, and compare this all sorting to the casual entry form [6-7]. This research describes the use of text retrieval with a combination of procedures to automatically discover accident features that can inform a better understanding of the providers to the accidents.

LITERATURE SURVEY

The rail transit is one of the tracking urban traffic systems. The survey focused on building a new rail transit system of line 1, in which Zhuhai was located in China. The corresponding three types of benefits are analyzed in the paper. First, the benefit of economics, which includes the time saving of passengers and value-added land, has been studied. Second, the kind of social benefits which reducing journey fatigue and reducing traffic accident benefits have been identifying according to the results. Third, they represent environmental benefits, which have been predicting the energy saving by using these benefits is analyzed, thus reducing the benefits of air pollution, and the CRTN model is used to predict the effect of noise from background environments. The authors made each effort to the public fully understand the external social interest and indirectly understand which the system of rail transit would bring up by using this system [8]. In Asia, the Indian railway is one of the largest railways, and this is the second world largest network, which is operated underneath by single management. Because of Speed, irresponsibleness, and capability, transportation became a prime suggestion for a railway. The cracks of rail should be modified and identified as soon as possible as it poses a heavy threat to the carriage of safe operations. The proposed system aims to eliminate the main issues in these sectors. This effective method had a continuous assessment and observation of rail tracks provide to stop an accident [9]. In recent years, the consumption of energy gradually increased the system of urban rail transit. This research is essential for metro system to analyze the data traction energy at the demand for improving efficient energy. According to the characteristics method of the subway, this research analyzes the consumption data of traction energy based on the classification and clustering methods. The energy data feature vectors are obtained after basically pre-processing the raw data. Cluster algorithms are useful to divide the feature vectors into numerous sets with similar characteristics. The energy pattern is generating by the decision tree algorithm. At last, the outliers of traction energy below the same energy model are chosen based on the local outlier factor (LOF). The investigation results show that the traction energy data can be separated into four patterns, and the outliers are detected under finer clusters than before, which can help the metro companies handle the energy data precisely [10]. The defects in the railway in the burning of rail insulated running rails were analyzed to develop the safety of rail traffic by the method of reducing the chances of rail accidents take place. The rail defects occurred from the electrical formation as well as the burning electrical formation of defects. The insulated electrical burning of rail joints emerges as a consequence of communication between the rail and the wheel, which leads to the formation of an arc. The result has been analyzed the reason for accidents and examined several spots as well as their electric-traction and electrical system [11]. The study focused on artificial intelligence (AI) to empower road vehicle train collision assessment of risk prediction, which lead to the expansion of avoiding collision system of the road to vehicle train system for unmanned railway crossing level. Objectives of the study revolve around the collision evaluated railroad risk, the collision risk, and prediction of severity model by using Gamma-log regression and Poisson techniques, respectively. The objectives of another study collision of modification implementing risk prediction factors to reduce the crossing collision vehicle to train risk. With the collision changes application on higher-level risk contributing factors that are ‘train visibility and 'crossing angle’, it predicts to diminish the road approximately 85% of collision vehicle-train risk [12].

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METHODOLOGY

Rail Signal Processing and Analyzing

Rail signals seek to analyze adversarial events with a view to prominence all the causes that contributed to the rate of a particular accident and therefore to avoid at least the imitation of new rail accidents and similar cases. Rail incident and accident investigation reports offer from the dataset of the UCI repository of big data for accident prevention. It would be appropriate to exploit these reports to extract the related information and recommend ways to avoid the imitation of adverse events. Fig. 1 shows the train disasters event (a) crash (b) derailed (c) fire in train and (d) track level crossing accidents.

Fig. 1: Train disasters event (a) crash (b) derailed (c) fire in train and (d) track level crossing accident

This result improved the probability of the wheel which is dislocated in the rails, which leads to an increased in need for maintenance of the railway. To determine the origins of these types of accidents, photo monitoring from several areas with regular burning was conducted. This methodology ceaselessly monitors the rail stress, estimates the results, and offers the rail break warnings such as bending of rails, possible buckling conditions, and wheel effect load revealing to the afraid authorities [13-16]. It seems logical to consider the practice of signal processing techniques and, in automatic learning, methods to recognize the environments and origins of accidents; therefore, proposed research solutions to avoid the reproduction of related insecurity events. Thus, the analysis of knowledge about rail accidents and events shares them among the proposed algorithm of learning sequences of detrimental events.

Deep Learning of TF-IDF

The fundamental procedure of rail accident fault full-text retrieval has applied the condition of when users searching input, segmenting word of the searching condition, and estimated the correlation between keywords of searching method and words in the lexicon to find words with correlation [16-21]. The next step is to looking for inverted lists according to those searching words and finally sorts the target file searching from index lists.

Accident of rail reports of fault text retrieve can be defined as a tuple model, describing index files, retrieving, and relationships between them, as F > D> Q> R.

Among them, D: Is a file collection, Q: Is a searching query, R: Shows correlation among file and D: and searching query Q. The Fig. 2 shows the overall proposed process of TF-IDF model.

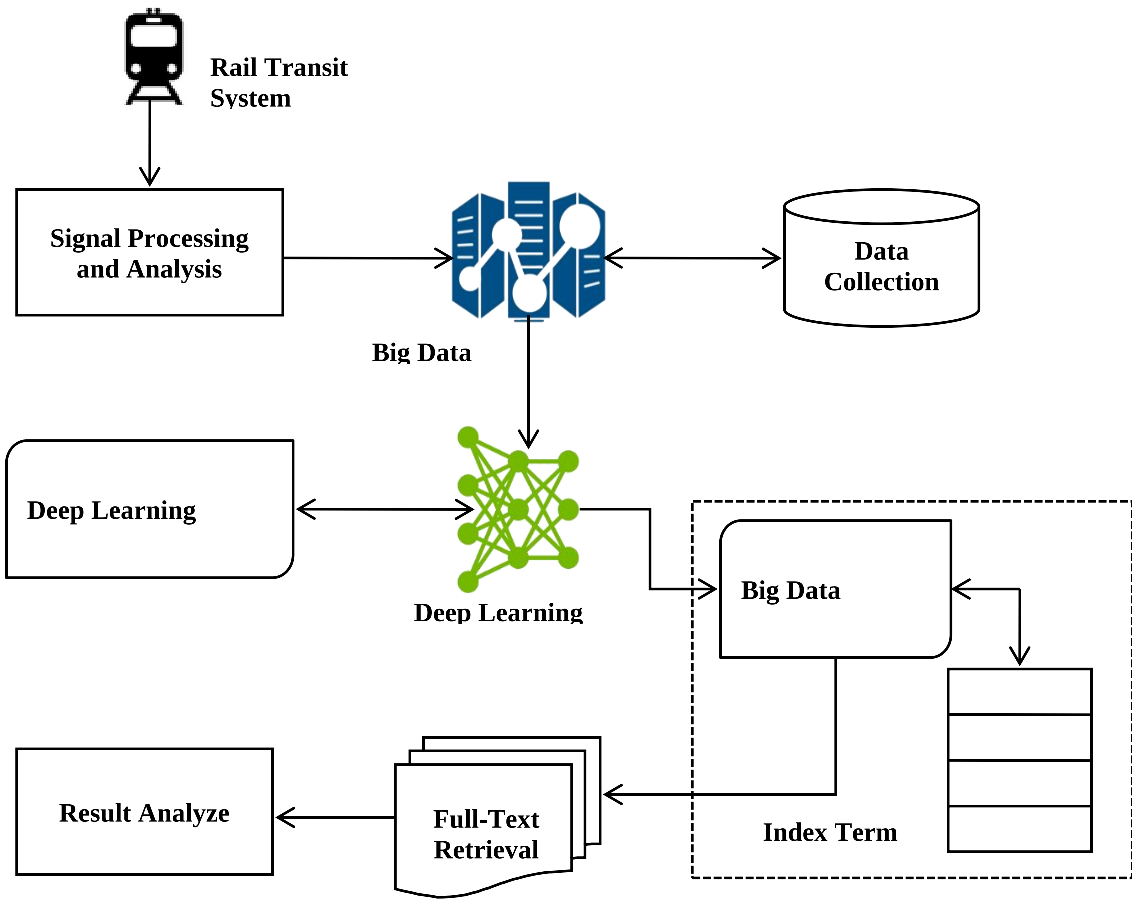

Fig. 2: Overall proposed process of TF-IDF

 https://doi.org/10.37896/pd91.4/91493

ISSN: 0369-8963

Term Frequency-Inverse Document Frequency (TF-IDF) is common in which a statistically weighted method and extensively used in text retrieval and text analysis. TF-IDF receives that if one word has a high frequency in one file while appears occasionally and then this word can be preserved as a keyword to distinguish this file from others. Term Frequency (TF) is a time word appearing in this file. Essentially a word with high existence is more interrelated with this file.

TF is defined as:

$$TF_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j} + 1} \tag{1}$$

In equation (1), n shows epochs word '$n_{k,i,j}$' shows the sum of all the words in the file,plus1istoavoid denominator is equal to zero.

Inverse Document Frequency (IDF) is defined as:

$$IDF_i = \log\left(\frac{S}{K_i + 1}\right) \tag{2}$$

In this equation, k_i shows the integer of file collection 'D', which word as w_ii sin, 'S' shows the size of 'D' and similarly, plus1isto avoid denominator is equivalent to zero. Combining TF with IDF is essentially using IDF to modify TF, which indicates the weight of the word w_i in filed j.

$$W_{i,j} = TF_i \times IDF_i \tag{3}$$

Algorithm 1: Deep Learning-Based Text Retrieval Process

Input:

D: the documents of the training set

T: the unique terms in all documents

Output:

Weight Matrix

Procedure:
1 for each term t_iЄ T do
2 for each document d_jЄ D do
3 wij = number of occurrences of term t_i in document d_j
4 End for of document
5 End for of term

 https://doi.org/10.37896/pd91.4/91493

ISSN: 0369-8963

Railway coincidence fault full text retrieve leads to retrieve and store text data effectively the railway using deep learning techniques for analyzing a better result for predicting rail accidents. Combined with segmentation, prediction, and relationship analysis with rules of a railway accident, fault advents may be exposed so that users in the field can avoid serious coincidences and protected daily procedures in the railway [22-27].

These extracted features based on regular expression and text structures this method to finds equivalent paragraphs based on consistent expressions and then this segment word and extracted features of content in those stored index terms. Features extraction needs to match with the index term of the dictionary, such as accident location dictionary, accident fault dictionary, and so on if there survive any unidentified words, which cannot be established and word extracted from dictionaries, then with the syntax structure, practice regular expression to extract the word.

Segmentation Process

Data classification has become a significant field in the proposed research due to the increased key procedures used for establishing the digital data by inevitably assigning a set of documents into predefined groupings based on their entire content. Including the dictionary matching model, word tagging model, word count model and deep learning methods and so on and ‘pj’ can be defined as a vector with word weights of unstructured entire text documents that were attainable in a digital form. It is measured as one of the equation (4).

$$p_j = < W_{1,i/}, W_{2,i/}, W_{3,i/}, ..., W_{n,i/} > \tag{4}$$

The document Segmentation process contains a set of phases; this can be accomplished with each phase using several techniques selecting appropriate techniques that should be used for each phase that affects the efficiency of performing a text classification process. The aim of the proposed text classification model that retrieves text more generality and efficiency by using the below equation can easily measure the weight value of vectors.

$$p_j = < W^{q}{}_{1,i/}, W^{q}{}_{2,i/}, W^{q}{}_{3,i/}, ..., W^{q}{}_{n,i/} > \tag{5}$$

Through the classification of unstructured documents of text step by step for a logical sequence with the support of simplification and efficiency process through the compatible integration of deep learning techniques for achieving a better performance to reach word segmentation of text data.

Full-Text Retrieval

The segmentation of words is stored in the index term of keywords that validate the index and full-text retrieval based on the algorithm of TF-IDF. This compares the retrieval time from the collected files. Full-text retrieval of rail accident fault tracking reports based on the similarity of query searching can effectively reduce retrieval time.

 https://doi.org/10.37896/pd91.4/91493

ISSN: 0369-8963

Algorithm 2: Deep learning method used forFull-Text Retrieval using TF-IDF

Input:

D: the documents of the training set
F: the selected Features set
TF: weight Matrix from text presentation phase

Output:

TF IDF weights:TF-IDF weights for selected features set

Procedure:

1 Reshape the columns of TF to match the selected features set

2 for each term t_i ЄF do

3   for each document d_jЄ D do

4   if TF_{ij}, not equal zero then df_i ++

5   End for of document log idfi)

6   idfi $= \log\left(\frac{D}{dfi}\right)$

7 End for the term

8 for each termt_i ЄF do

9   for each document d_jЄ D do

10   TF-IDF_{ij} = TF_{ij} + idf_i

11   End for of Document

12 End for of term

https://doi.org/10.37896/pd91.4/91493

ISSN: 0369-8963

The index term is used to easily analyze the similarity text while retrieving this will save time and easy to search query finally user can easily predict the rail accident which was analyzed by the cause of accidents that occurred repeatedly.

$$sim(q, p) = \frac{\sum W^{q}{}_{i,j} \times W_{i,j}}{| q_i \times p_i |} \tag{6}$$

The proposed research has been developed for predicting a rail accident by analyzing the probability of a rail accident event occurred. The cause of rail accident reports is retrieved by using the query search of full-text retrieval from the storing of index term, which was derived from the segmentation process. The TF-IDF method of deep learning is used to search queries from big data more efficiently to predict the safety of rail accidents.

RESULTS AND DISCUSSION

Railway accident reports of events are typically unstructured text data, recording significant information of fault or accidents, such as time, reason, location, and part of responsible so on. From the year 2010-2019 an accident of fault tracking reports is accomplished with full-text retrieval with similarity search of index term. Using the TF-IDF deep learning algorithm used to analyzed and classify the cause of rail accidents, these techniques are used to predict the safety of accidents.

Number and Type of Accidents

By far, the highest number of accidents occurred because of derailed and fire in train accidents. The other type of accidents includes crash, cross-level, and miscellaneous of a train, etc. But their number is relatively much lower in the type of accident. There are 1000 total numbers of percentages of rail accidents are calculated by the classification of causing rail accidents. Table 1 show the total number of accidents occurred during the year of 2009-2019 and the Fig. 3 shows the detailed chart for number of accidents occurred for various reasons. The Fig. 4 shows the percentage of number of accidents occurred by its type.

Table 1: Total number of an accident occurred during the year of 2009-2019

Causes for rail accident	Total number of accident
Crash	77
Derailed	403
Fire in Train	379
Cross-level of train	82
Miscellaneous of train	59
Total	1000

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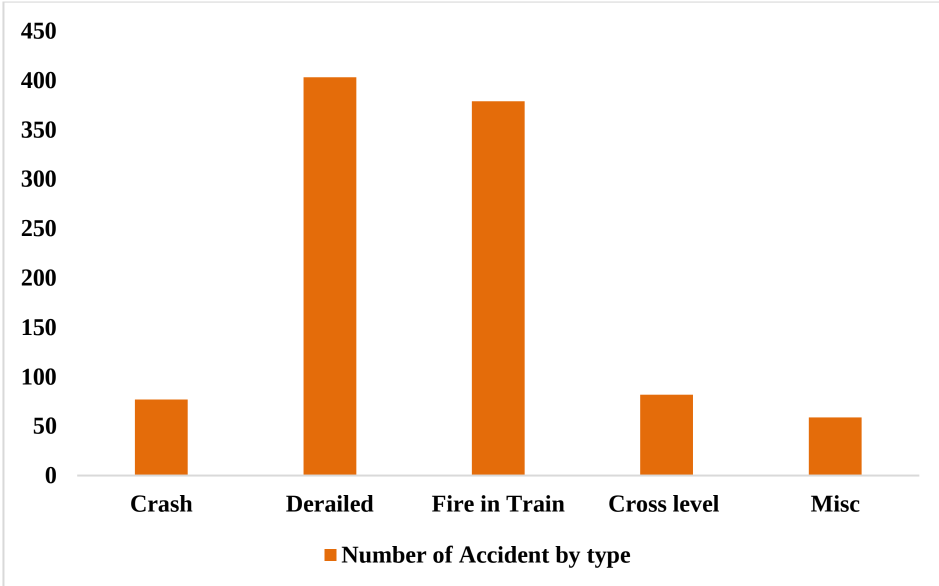

Fig. 3: Chart for the number of an accident occurred for a reason

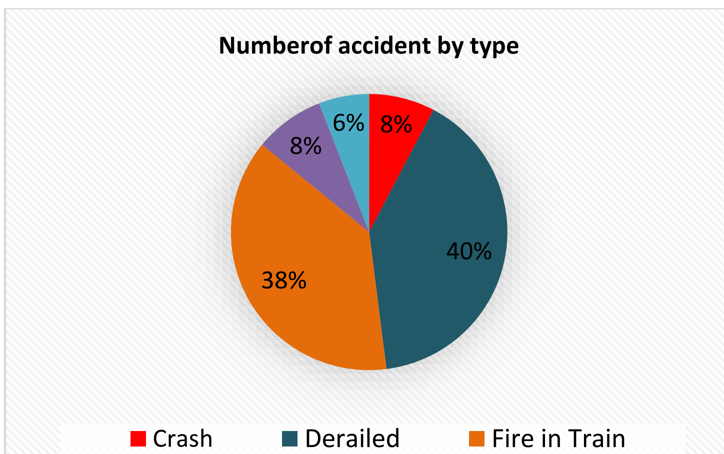

Fig. 4: Percentage of number of the accident occurred by its type

Train Accidents per Million Kilometres Run

The trains of the Railways are clocking more passenger-kilo-meters each year. From 2.08 lakh million kilo-meters, the number of passenger kilo-meters reached 12.37 lakh million kilo-meters in 2010-19 the rail incidents. Train Accident with the percentage of 0.15, 0.13, 0.12, 0.11, and 0.13. The Fig. 5 shows the calculated year-wise train accidents from 2010-2019".

ISSN: 0369-8963

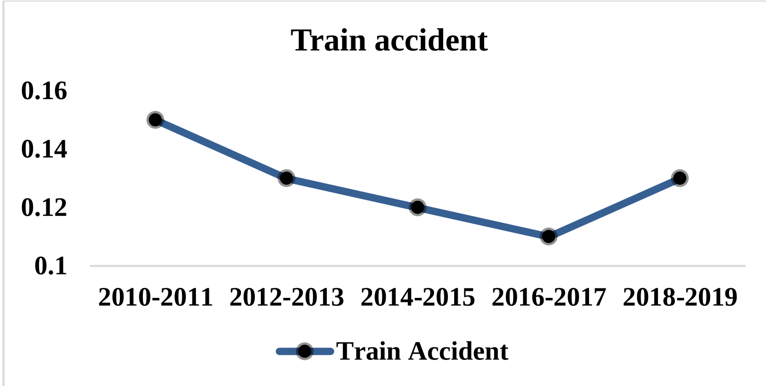

Fig 5: Year-wise train accident calculated

There are several reasons the train accident occurred in the dataset of the proposed method to analyze the type of accident with a percentage.

Number of Casualties

Though the number of accidents in 2010-2019 was more than the number of accidents that occurred, were the overall chart there are passed away around 500 peoples. The accidents more fatal compared to the other years, 2016-207 there are a maximum number of people injured and died. The number of those killed has been on the decline since 2010-2019. The Table 2 shows the year wise causalities analysed from 2010-2019. The Fig. 6 shows the total number of causalities analyzed year wise in bar chart".

Table 2: Year-wise casualties analyzed

Duration	Injured	Died
2010-2011	188	119
2012-2013	93	41
2014-2015	159	60
2016-2017	235	279
2018-2019	230	98

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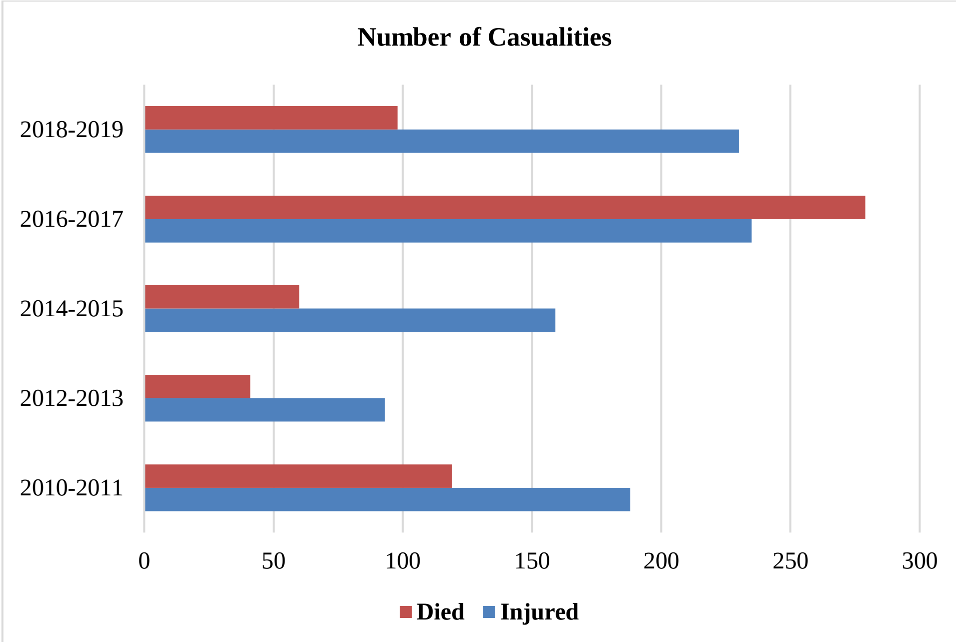

Fig. 6: Total number of causalities analyzed year wise

Casualties per Million Passengers Carried

From the casualties of million passengers, the number of originating passengers reached 0.05 million in 2010-2011. Except for 2012-2013, this parameter was more or less constant at 0.09. In 2013-2015, it took 0.05 owing to a high number of casualties. While it decreased to 0.03 in 2016-2017, it increased to 0.06 in 2018-19 because of a higher casualty shown in Fig. 7.

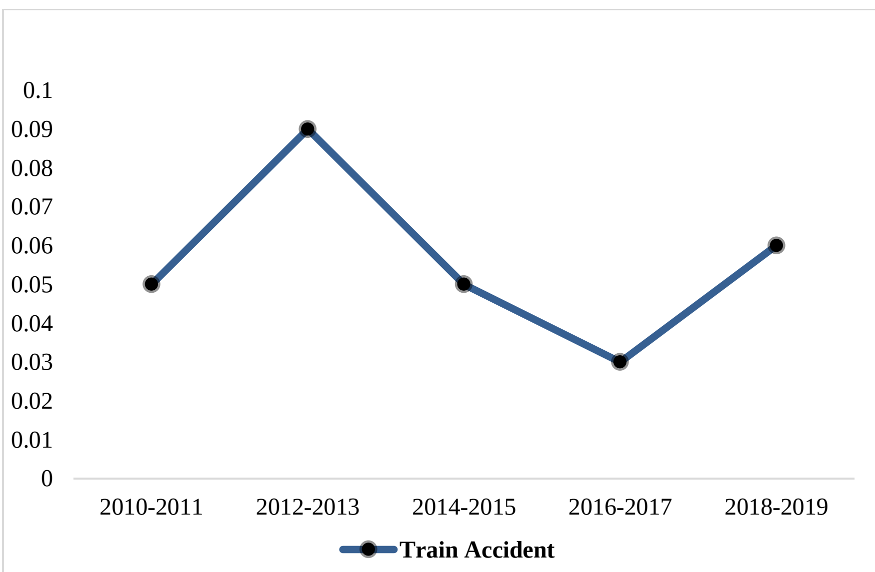

Fig. 7: Causalities per million passengers carried

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Cause of Accidents

There have been various causes for rail accidents ranging from Human Failure to Sabotage to Equipment Failure etc. In the year 2010-2019, human failure has caused more than 86% of the total accidents. Due to the railway staff and others which mean the human error caused accidents from the data. The Fig. 8 illustrated various method of accident happening by comparing other types of accidents". Fig. 9 shows the percentage-wise cause of accidents".

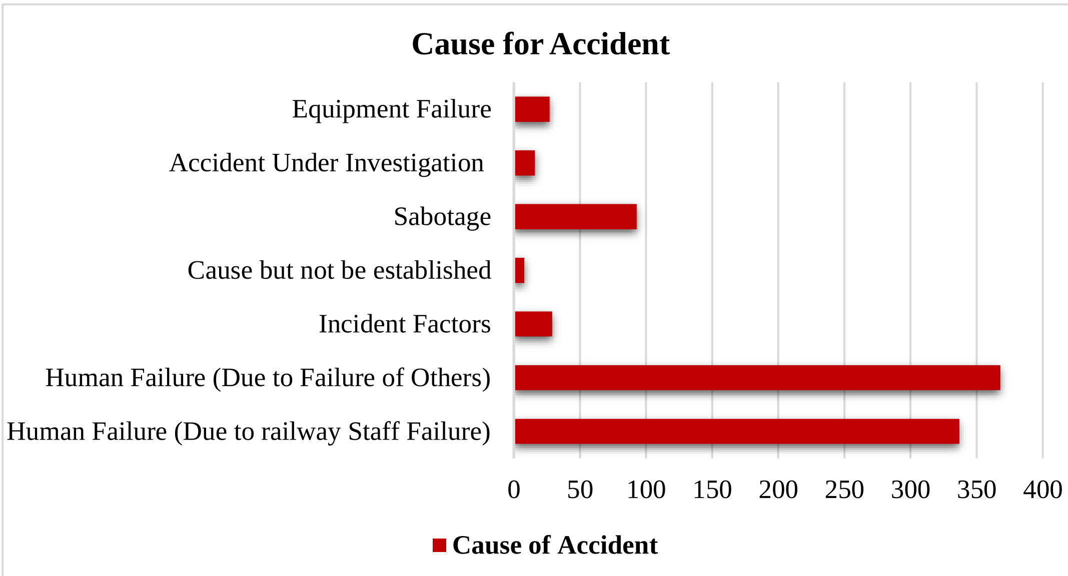

Fig. 8: Classify the cause of the accident

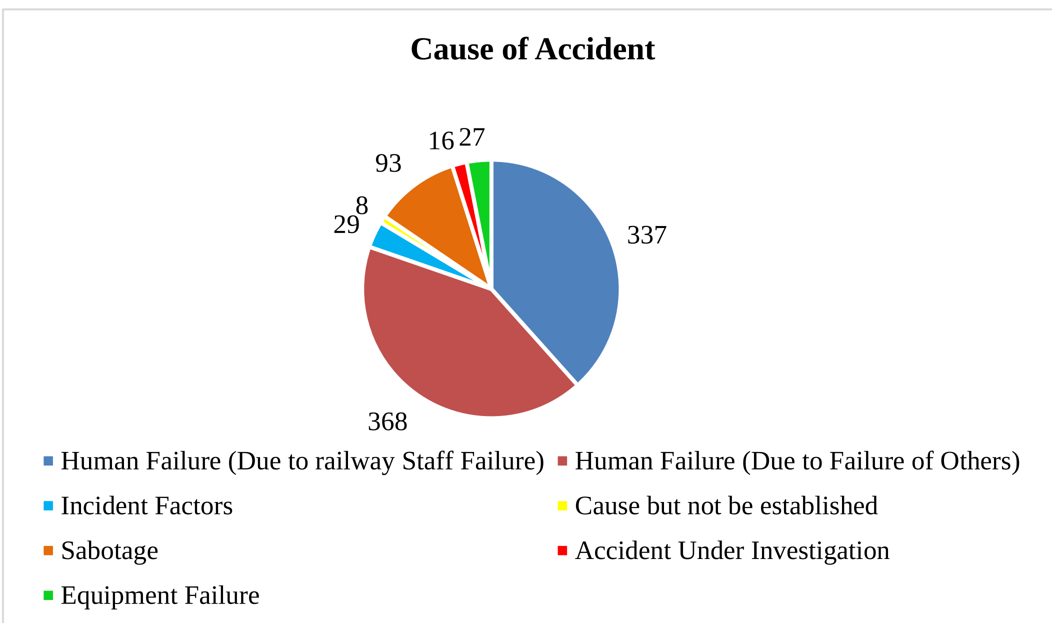

Fig. 9: Percentage-wise analyzing the cause of accidents

ISSN: 0369-8963

Efficient Classification of Full-Text Retrieval

The below Fig.10 demonstrated the feature classification of rail accident reports" using the proposed algorithm of TD-IDF used to detect full-text retrieval by using several segmentation of query level which was compared with existing algorithms.

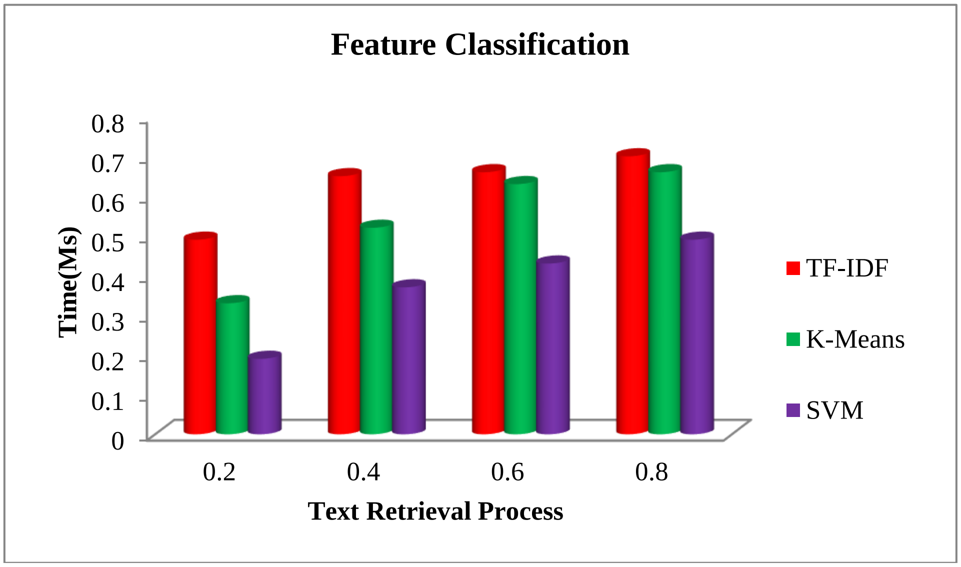

Fig. 10: Proposed method of segmenting full-text retrieval

Efficient rail fault accidents and incidents are caused due to tremendous reason in the overall process. The railway accident, especially full-text retrieval of searching query process for a maximum probability of accident occurred. The new advanced technology of deep learning of the TF-IDF algorithm is used to retrieve text from analyzing signal processing of the railway report.

CONCLUSIONS

The research proposed for the solution of accident fault full-text retrieval and analysis based on the introduction of segmentation, index inverted, and text retrieval to achieve text segmentation from unstructured text data of big data. And the proposed system, the railway report of an accident that occurred in rail, is the experimental output, which offers almost real-time retrieval of a key accident. Meanwhile, integrating with new technologies of deep learning method is used to construct a railway from the platform of big data with unstructured railway data with text retrieval. And finally, analyzing the similarity of an accident that occurred with the aid of the TF-IDF method is used to analyze the entire process of deep learning techniques. The report of railway accidents and causes of accidents are analyzed from the experimental result of outcomes this illustrated the safety measure of the railway line. The proposed method of deep learning is used to analyze the accident of rail and, by full-text retrieval, can easy to predict the accident of rail.

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