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Applications of machine learning methods for engineering risk assessment – A review

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ABSTRACT

The purpose of this article is to present a structured review of publications utilizing machine learning methods to aid in engineering risk assessment. A keyword search is performed to retrieve relevant articles from the databases of Scopus and Engineering Village. The search results are filtered according to seven selection criteria. The filtering process resulted in the retrieval of one hundred and twenty-four relevant research articles. Statistics based on different categories from the citation database is presented. By reviewing the articles, additional categories, such as the type of machine learning algorithm used, the type of input source used, the type of industry targeted, the type of implementation, and the intended risk assessment phase are also determined. The findings show that the automotive industry is leading the adoption of machine learning algorithms for risk assessment. Artificial neural networks are the most applied machine learning method to aid in engineering risk assessment. Additional findings from the review process are also presented in this article.

1. Introduction

In recent years, machine learning algorithms have aided in solving domain specific problems in various fields of engineering from detecting defects in reinforced concrete (Butcher et al., 2014) to monitoring natural disasters (Pyayt et al., 2011). The increase in the use of machine learning algorithms may be attributed partly to an unprecedented increase in the development and use of industrial internet of things (IIoT) (Lund et al., 2014). IIoTs allow collection of data for a given application without the need for human intervention during operations. The data collected by the IIoTs can be studied by data-driven techniques to create added value in various fields of engineering (Yin et al., 2015).

Simultaneously, development and use of autonomous vehicle systems, such as autonomous automobiles, autonomous surface marine vehicles and unmanned aerial drones are also on the rise (Lozano-Perez, 2012; Advanced Autonomous Waterborne Applications, 2016; Federal Aviation Administration, 2018). Autonomous vehicular systems are equipped with wide variety of sensors generating data, which needs to be processed in real-time. The question arises, how will these trends affect engineering risk assessment? Risk assessment here can be defined as "*the overall process of risk identification, risk analysis and risk evaluation*" (The International Organization for Standardization, 2018).

Currently, the field of engineering risk assessment is at a crossroad. Although, there are about thirty different risk assessment techniques (International Organization for Standardization, 2009), the ability to perform real-time risk assessment is limited. In traditional risk assessment techniques, the propagation of risk is assumed to occur in time-scales, such as months or years. For example, a Failure Mode Effect & Criticality Analysis (FMECA) does not consider any dynamic changes in the process/product being assessed until the next mandatory analysis. As industrial need for real-time risk assessment increases, use of machine learning algorithms may also increase.

Fig. 1 shows that the field of machine learning is a subset of artificial intelligence (AI) and deep learning is a subset of machine learning. The term data science is a field using techniques from AI, machine learning, deep learning and computer science. According to Mitchell (1997) a computer is said to learn from experience *E* with respect to some class of tasks *T* and performance *P,* if its performance at tasks in *T*, as measured by *P*, improves with experience *E*. In the last few years, approaches used to perform risk assessment can be observed to be changing as machine learning algorithms are beginning to aid and improve the findings from traditional risk assessment techniques.

Applications, such as processing vehicle accident data to predict crash severity for a given location (Li et al., 2008), processing textual data to identify key messages in accident investigation reports (Marucci-Wellman et al., 2017a, 2017b) are some of the studies published in recent risk and safety focused journals. Nevertheless, there

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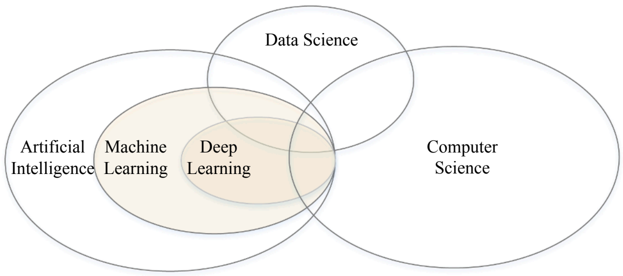

Fig. 1. Venn diagram representing the components of AI adapted from Goodfellow et al. (2016).

may be limitations associated to the adoption of machine learning in risk assessment. For example, do these different terminologies affect the way machine learning is perceived and used to aid risk assessment?

A thorough review of machine learning applications for engineering risk assessment does not exist in the literature. Therefore, a structured review is needed to answer research questions, such as "Which machine learning method is adopted the most for risk assessment"; "Which industry is leading the adoption of machine learning for risk assessment"; "How is machine learning being implemented and verified to be suitable for risk assessment"; "Are there geographical trends in the adoption of machine learning for risk assessment"; "What kind of data is used to develop the machine learning algorithms to be used for risk assessment"; "Which risk assessment phase can be aided by use of machine learning"; and "What trends can be observed with respect to journal publications in this new field".

The aim of this article is to provide a comprehensive and a structured review of literature using machine learning to perform or aid in risk assessment and to find answers to the above research questions. The main contribution of this article is the presentation of the current state of the art in risk assessment using machine learning algorithms. The findings from this article may enable risk practitioners in academia and the industry to learn form a wide variety of machine learning applications for risk assessment in different industries.

The article is structured as follows. Section 2 presents the structured method used to perform the literature review and the approach used to obtain the citation dataset. Section 3 presents the results of the review followed by the discussions in Section 4. Concluding remarks are presented in Section 5.

2. Method

This section presents the method used to retrieve relevant literature from publicly available citation databases. For each step in the process, explanation of the employed approach is described in this section. It also introduces the approach used by the authors of this article to classify the selected literature into different categories.

2.1. Literature survey process

Fig. 2 illustrates the literature retrieval process employed in this paper. In Step 1, keywords describing the subject matter are identified. Trial keyword searches showed that the citation databases, such as Web of Science and Google Scholar performed poorly with inconsistent and sparse results when compared to Scopus and Engineering Village. Therefore, Scopus and Engineering Village were selected as the citation databases in this paper.

Machine learning and risk assessment are two broad fields of study with different use cases. As shown in Fig. 1, the field of machine learning is interrelated with AI, deep learning and data science. Similarly, the field of risk assessment lacks the use of standardized terminologies, resulting in varied contextual definitions of risk and safety (Rausand, 2013). To ensure all relevant literature are captured through

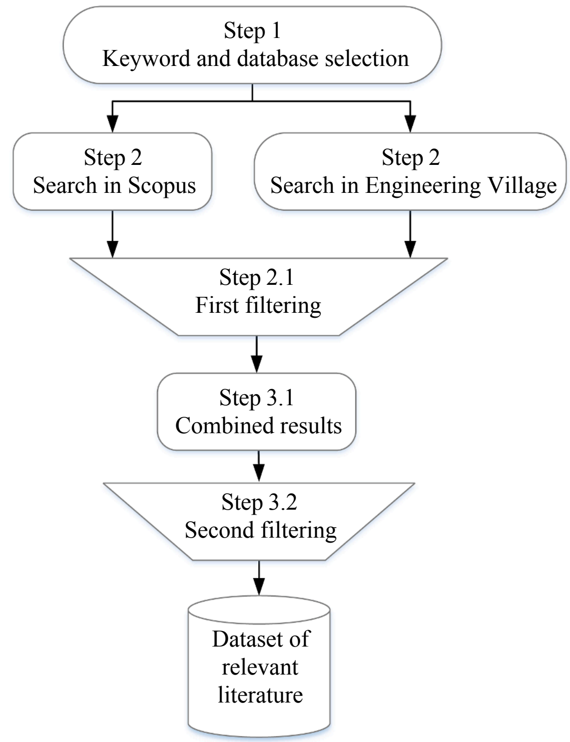

Fig. 2. Literature retrieval process.

the literature retrieval process, different unique search keywords are required. This was true also during the trial searches, where strict keywords such as *"machine + learning and risk + assessment"* did not result in relevant literature. Therefore, a combination of keywords is necessary. The identified keywords are combined using logical operators to ensure that they follow the format required by the search engine of Scopus and Engineering Village. Table 1 lists the chosen keywords used to search the relevant articles.

In addition to the keywords in Table 1, relevant filters in Scopus and Engineering Village are chosen to avoid duplicate entries and limit the scope to engineering fields. For example, the search results from Engineering Village are a union of Compendex and Inspec databases. Therefore, filters to remove duplicates were selected accordingly.

In Step 2, the keyword search was performed in Scopus and Engineering Village. In Step 2.1, to limit scope of the search results, a filtering process was employed by evaluating the search results against four selection criteria. The four criteria are described in Table 2. Although conference articles may propose newer interesting methods, including them in this review would have resulted in a large corpus of articles. Filtering and reviewing these articles would also require lot of more time and resource. Therefore, Criterion C3 was laid out to limit the scope of the study to only review published journal articles.

In Step 3.1 the database obtained from the first filtering process is combined and duplicates from the combination of Scopus and Engineering Village datasets are deleted. To narrow the search results, a second filtering process was performed in Step 3.2. The two criteria in

Table 1
List of search keywords used in Scopus and Engineering Village.

No.	Selected search keywords
1	Machine Learning AND Engineering AND (Risk OR Safety)
2	Artificial Intelligence AND Engineering AND (Risk OR Safety)
3	Data Mining AND Engineering AND (Risk OR Safety)
4	Big Data AND Engineering AND (Risk OR Safety)
5	Data Fusion AND Engineering AND (Risk OR Safety)

Table 2
Criteria used in the first phase (Step 2.1) of the literature filtering process.

Criterion	Description
C1	The article should be written in English.
C2	Studies indexed in database other than Scopus or Engineering Village are out of scope.
C3	Only journal articles are considered. Conferences papers are out of scope.
C4	Only articles using AI/machine learning algorithms for risk assessment are selected.

Table 3
Criteria used in the second phase (Step 3.2) of the literature filtering process.

Criterion	Description
C5	Focuses on risk identification, analysis or evaluation. Focuses on risk-based control/system feedback.
C6	Focuses on machine learning or deep learning methods. AI based methods, such as expert systems, genetic algorithm, search problems and Bayesian belief networks are out scope.

the second filtering process are C5 and C6 as described in Table 3. The filtered dataset from Step 3.2 resulted in the sample space of articles focusing on risk assessment using machine learning algorithms.

2.2. Literature classification

The dataset of relevant literature contains vital information regarding various aspects of the use of machine learning in risk assessment, such as the type of industry, the type of machine learning method used, and the type of risk assessment phase targeted etc. These aspects may provide better insight into suitable machine learning algorithms used to perform risk assessment for different applications and therefore, need to be investigated.

To answer the research questions, the required information was retrieved from the chosen literature by both reviewing the contents of the articles and by utilizing the meta-data properties of the article's citation. The authors of this article have classified the chosen articles with respect to the location of the affiliated institute, the type of the journal article, the type of industry, the phase of risk assessment focused on, the type of implementation, the machine learning method used, and the type of input data utilized.

2.2.1. Location of affiliations

To gain a global overview, the location of the institute affiliated to each article is tabulated. This process results in a country level distribution of scientific contributions giving insights into the global publication trends in this field.

2.2.2. Type of journal article

The type of journal article was classified by using both the metadata information and by reviewing the articles. Two questions are answered resulting in two different classifications. First, is the article a review or an original research article? Second, is the article published in a subscription-based journal or in an open source journal?

2.2.3. Risk assessment phase

Each article was reviewed and categorized with respect to the risk assessment phase under focus. According to International Organization for Standardization (2018), the three risk assessment phases are risk identification, risk analysis and risk evaluation. International Organization for Standardization (2018) defines risk identification as the process of identifying potential risk factors. Therefore, for an article to be categorized into the risk identification phase, the article needs to focus on identifying potential risks in the given context of the article. For example, Tango and Botta (2013) propose classifiers to identify driver distractions when driving a car. Driver distraction can be categorized as one of the potential risk factors encountered during driving. Therefore, contributions from Tango and Botta (2013) are categorized into the *"risk identification"* phase.

Risk analysis is a process to comprehend the nature and determine the level of risk (International Organization for Standardization, 2018). Articles that utilized machine learning methods to comprehend the nature and determine the level of risk are classified as articles focusing on the risk analysis phase. For example, Mojaddadi et al. (2017) propose an ensemble machine-learning approach to determine the level of risk of flood for a given geographical area.

Risk evaluation is defined as the process of comparing the results of risk analysis with risk criteria to determine whether the risk and/or its magnitude is acceptable (International Organization for Standardization, 2018). For example, Curiel-Ramirez et al. (2018) evaluate the risk of crashing a car into the vehicle in front and suggest a maneuver to the driver. Many articles also focus on a combination of two or more risk assessment phases in their proposed applications. For example, Farid et al. (2019) focus on identifying, assessing and evaluating safety performance functions. Therefore, contributions from Farid et al. (2019) are classified under the risk identification, risk analysis and risk evaluation phases of risk assessment.

2.2.4. Type of implementation

Publications can be classified with respect to the type of implementation of machine learning methods to perform risk assessment. The authors of this article have classified the articles into five different classifications when considering the type of implementation, namely case-study, real-world implementation, experimental tests, simulator tests, and review.

Articles testing the proposed method with a given case-study are classified into the *"case-study"* category. For example, Bevilacqua et al. (2010) use a case-study approach to test seven different data mining techniques to illustrate important relationships between risk level, root causes and correction actions. Articles that implement their proposed method in real-life systems are categorized into *"real-world implementation"* category. For example, Curiel-Ramirez et al. (2018) implement the proposed method for real-time steering-wheel movement to follow the car in front. Articles also use experimental tests to validate the proposed methods, such articles are therefore classified into the *"experimental tests"* category. For example, Kumtepe et al. (2016) validate their proposed method through experimental tests to detect driver aggressiveness. Articles also use simulator tests to validate their proposed method, such articles are classified into *"simulator tests"* category. For example, Hu et al. (2017) use simulator tests to gather road scenario data and use the generated data to suggest maneuvers to the driver. The result of the literature search also includes of review articles. Such articles are classified into the *"review"* category. For example, Elnaggar and Chakrabarty (2018) provide a comprehensive review of the machine learning methods applicable in the cyber security industry.

2.2.5. Type of machine learning method and input data used

Different machine learning methods are used in the literature to perform risk assessment. An industry-wise distribution of the methods used can uncover trends in the adoption of the different machine learning methods. In addition, each article may also use different inputs to train the machine learning algorithm. The format of the input data used and the input data acquisition approaches are also classified. Format of the input data can be ‘video data’, ‘sensor data’, ‘textual data’ etc. Input data acquisition approaches could be historical, real-time or a combination of historical and real-time data. The authors have also identified the machine learning methods used, the input formats used, and the data acquisition approaches used in the chosen literature.

3. Results

This section presents the findings from the literature review process described in Section 2. After the first filtering process, the dataset consisted of citation meta-data of 291 articles. Some articles did not clearly focus on the phases of risk assessment or machine learning in specific and were consequently eliminated during the second filtering process using the criteria C5 and C6 as listed in Table 3. The final literature dataset consists of 124 articles.

3.1. Relevant literature

This subsection presents some of the interesting studies found among the 124 articles. Overall, the articles can be divided into three different types, articles focusing on learning from textual data, articles focusing on learning from numerical data, and articles providing a review of the state-of-the-art.

3.1.1. Learning from textual data

In many industries, safety incidents or accidents are reported in a textual format, either by the use of standard questionnaires or free text documents. This practice creates large text corpora, which contain rich narratives of safety incidents or accidents. Processing these texts can benefit identification, analysis, and evaluation of risks in different industries. This need is evident in the literature, where numerous methods are proposed to process textual data, some of which are chronologically described in this subsection.

The period between incident reporting, clearance time, and road clearance can be predicted by processing information rich textual data using machine learning algorithms, such as artificial neural network (ANN), support vector machine (SVM), decision tree (DT), latent dirichlet allocation (LDA), radial basis function (RBF) (Pereira et al., 2013). Robinson et al. (2015) propose the application of latent semantic analysis (LSA) to infer higher-order structures between accident narrative documents and showed that LSA can capture contextual proximity of an accident narrative. Tixier et al. (2016a) investigate the use of natural language processing (NLP) to ease the accident coding process of textual unstructured accidents reports.

Brown (2016) analyzes textual accident data and investigate the factors contributing to extreme rail accidents by utilizing LDA. Tixier et al. (2016b) apply random forests (RF) and stochastic gradient tree boosting (SGTB) to a large pool of textual accident data. The input features and categorical safety outcomes are extracted by using NLP. The proposed models can predict type of injury, energy type, and injured body parts. Further, Tixier et al. (2017) use NLP to process 5298 raw accident reports to identify the attribute combinations that contribute to injuries in the construction industry. Marucci-Wellman et al. (2017a, 2017b) use machine learning to classify injury narratives to the format found in Bureau of Labor Statistics Occupational Injury and illness event leading to injury classifications for a large workers compensation database.

3.1.2. Learning from numerical data

Risk and safety relevant data is also found in numerical formats, be it accident frequencies or other time-series data. By processing the numerical data, machine learning can provide insights into the different factors influencing safety and risk, some of the interesting contributions are chronologically described in this subsection.

Sohn and Lee (2003) compare ensemble algorithms to fusion algorithms and a clustering algorithm to classify Korean road accident data. Chang and Chen (2005) develop a classification and regression tree (CART) to establish the empirical relationship between traffic accidents and highway geometric variables, traffic characteristics and environmental variables. Liang et al. (2007) propose a method to detect real-time cognitive distraction of drivers using drivers’ eye movements and driving performance data. The results show that the SVM classifier outperformed the logistic regression model. Rajasekaran et al. (2008) investigate the application of support vector regression (SVR) to forecast risky ocean storm surges.

Sugumaran et al. (2009) develop a DT to assess the safety of the structure when subjected to varying vibration amplitudes. Experimental results show that DTs can highlight the importance of various input variables influencing the excitation of a physical structure. Ma et al. (2009) propose a real-time highway traffic condition assessment using vehicle information using SVMs and artificial neural networks (ANNs). The reported results show that performance of SVMs are superior in terms of predicting detection rate, false-alarm rate, and detection times. Wang et al. (2010) utilize a semi-supervised machine learning method to develop a dangerous-driving warning system. Mirabadi and Sharifian (2010) propose the application of association rules to reveal unknown relationships and patterns by analyzing 6500 accidents on Iranian Railways.

Kashani and Mohaymany (2011) identify the factors influencing crash injury severity on Iranian roadways using CART. The model classifies incidents into three-classes. Improper overtaking and not using seatbelts are found to be important factors affecting the severity of injuries on Iranian roadways. Siddiqui et al. (2012) utilize CART and RF to investigate important variables of accident crash data per traffic analysis zone for four counties in the state of Florida. Variables, namely the total number of intersections, the total roadway length with 35 mph posted speed limit (PSL), the total roadway length with 65 mph PSL, and the light truck productions and attractions are identified to greatly influence both the total number and the severity of crashes. Ding and Zhou (2013) propose a risk-based ANN early warning system applicable during the construction of urban metro lines in China. Tango and Botta (2013) compare the performance of ANN, SVM, and logistic regression to detect visual distraction of drivers by using vehicle dynamics data. In this study, SVM classifier is reported to outperform the other machine learning methods in simulator-based tests.

Li et al. (2014) apply SVM and principal component analysis (PCA) to process historical maintenance data and to aid condition-based maintenance objectives. Tavakoli Kashani et al. (2014) investigate the use of CART to analyze the injury severity of motorcycle pillion passengers in Iran. Fatality of motorcycle passengers are linked to risk factors, such as the type of area, land use, and the injured part of the body. Mistikoglu et al. (2015) utilize DTs to extract rules that show the associations between inputs and safety outputs of roofer fall accidents. The proposed DT showed that chances of fatality decreased with adequate safety training, but increased with increasing fall distance. ANNs are also used to develop generic decision support systems (Bukharov and Bogolyubov, 2015). Kwon et al. (2015) propose naïve bayes (NB) and DT classifiers to identify relative importance between risk factors with respect to their severity level. DTs are reported to perform better than NB on the accident dataset from California Highway Patrol. The results found that collision type, violation category, movement preceding collision, type of intersection, and location of state highway were highly dependent on each other. Weng et al. (2015) proposed a binary probit model to assess driver’s merging behavior and rear-end crash risk in work zone merging areas. The result show that rear-end crash risk can increase over the elapsed time after a merging event has occurred. Pawar et al. (2015) propose the use of SVMs to classify performance and safety of uncontrolled intersections and pedestrian midblock crossings. The proposed SVM is reported to predict accepted gap values relatively better than the binary logit model. Salmane et al. (2015) propose a hidden Markov model (HMM) to detect and evaluate abnormal situations induced by road users (pedestrians, vehicle drivers, and unattended objects) at level crossing environments.

Wang et al. (2016a, 2016b) compare the capabilities of Poisson regression, negative binomial regression, regularized generalized linear model, and boosted regression trees (BRTs) to develop safety performance functions. Ding et al. (2016) utilize gradient boosting logit model to study driver stop-or-run behavior by using data from loop detectors at three signalized intersections. Aki et al. (2016) propose an NB classifier to classify six road surface conditions based on laser radar sensors. The article aims to increase safety by detecting lane markings for automatic platooning system, such as autonomous trucks. Relative performance of kernel regression and negative binomial model for a given accident dataset is investigated by Thakali et al. (2016). Findings show that kernel regression outperforms the negative binomial model.

Moura et al. (2017) utilize self-organizing maps (SOMs) to convert high-dimensional accident data into easy to infer graphical representations. Ding et al. (2017) propose an apriori based early risk warning system called dispatching fault log management and analysis database system (DFLMIS). The aim of DFLMIS is to process the large-scale log-data obtained by the Shanghai Shentong Metro Dispatch. Jamshidi et al. (2017) propose an automatic detection of squats in railway tracks using images. The visual length of the squats is used as input to a form of ANN called convolution neural network (CNN). The failure risk is estimated by studying the growth of squats on a busy rail track of the Dutch railway network. Density-based spatial clustering of applications with noise (DBSCAN) and kernel density estimation methods are proposed to accurately predict maritime traffic 5, 30, and 60 min ahead of time by Xiao et al. (2017). Zhen et al. (2017) propose a framework to perform multi-vessel collision risk assessment and investigate the performance of DBSCAN algorithm on the maritime traffic dataset from the west coastal waters of Sweden. Xiang et al. (2017) propose a fuzzy neural network (FNN) to assess onboard system risk of underwater robotic vehicles and suggest appropriate fault treatment.

Farid et al. (2018) propose the K-nearest neighbor (KNN) method for calibrating safety performance functions to evaluate road safety for four states in the USA. Zhu et al. (2018) use RFs and ANNs to classify driver injury patterns resulting from single-vehicle run-off-road events into four levels, namely fatal/serious injury, evident injury, possible injury, and no injury. Chen et al. (2018) propose use of logit model to analyze hourly crash likelihood in given highway segments. Temporal environmental data, such as road surfaces and traffic conditions are also included as inputs. Xu et al. (2018) propose the use of association rules to investigate the factors contributing to serious traffic crashes and their interdependency on Chinese roadways. Kolar et al. (2018) propose the use of CNNs to detect safety guardrails in construction sites. The input data (images) are augmented by overlaying 3D models of virtual guardrails to create a large dataset and a transfer learning approach is used to detect the presence of guardrails in new images. Wang and Horn (2018) propose a risk-based image recognition system to detect and track headlamps of cars in night traffic using least squares regression (LSR).

Goh et al. (2018) evaluate the relative importance of different cognitive factors mentioned in the theory of reasoned actions (TRA), which can influence safety behavior. DT, ANN, RF, KNN, SVM, linear regression (LR), and NB are used to predict the percentage of unsafe behavior. Data is sourced from 80 construction workers through a questionnaire and through behavior-based safety (BBS) observation data. The results show that DTs perform better on the dataset with an accuracy of 97.6%. Jocelyn et al. (2018) use logical analysis data (LAD) approach to extract knowledge and to characterize accidents involving heavy machinery. Cortez et al. (2018) utilize a form of ANN called recurrent neural networks (RNNs) to predict emergency events involving human injuries or deaths by analyzing historical police reports on emergency events. Kaeeni et al. (2018) propose the use of machine learning algorithms, such as ANN, NB and DT together with a genetic algorithm to classify different train derailment incidents in Iran. Farid et al. (2019) compare the performance of different machine learning methods to model safety performance functions (SPFs). The article evaluates road safety in seven states in the USA before and after countermeasures are deployed. The results show that a hybrid model using Tobit, RF, negative binomial and hybrid models perform better than other methods.

3.1.3. Review articles

Faouzi et al. (2011) present a survey of existing methods in data fusion and machine learning applicable for intelligent transportation systems (ITS). Young et al. (2014) provide a review of past, current and future approaches in simulation modelling in the road safety industry. Halim et al. (2016) present a thorough review of artificial intelligence techniques applicable for predicting accident or unsafe driving patterns. The potential of machine learning in predicting driver behavior and road safety is also addressed. Choi et al. (2017) investigate opportunities and challenges of big data on technological development of industrial-based business systems. Huang et al. (2018) present the opportunities and challenges of using big data in accident investigations. Ouyang et al. (2018) propose the connotation of safety big data (SBD) and explain its rules, methods, and principles. Nine principles of SBD are highlighted with their relationships to data processing flow. Lavrenz et al. (2018) provide a comprehensive review of time-series analysis methods to be applied on high-resolution traffic safety data. Suitable machine learning algorithms applicable to hardware security are reviewed by Elnaggar and Chakrabarty (2018). Ghofrani et al. (2018) provide a review of recent research development in the field of big data analysis focusing on operations, maintenance, and safety aspects of railway transportation systems.

3.2. Results obtained from citation information

This subsection presents the statistical results obtained from processing the citation *meta*-data of the reviewed literature. The citation *meta*-data of the 124 articles were processed using the Pandas library in Python programming language (McKinney, 2010).

Table 4 shows the distribution of articles published in the journals. Journal of Accident Analysis and Prevention and Journal of Safety Science and are the two leading journals, which have together published over 16% of published papers focusing on use of machine learning for risk assessment. Only one among the top fifteen journals (Sensors) is an open-access journal.

The citation database is processed to retrieve a distribution of authors contributing to this field. Both first authorship and co-authorships are considered as the basis for calculating the author contributions. Table 5 lists the top ten researchers with their frequency of contributions. It is observed that out of 422 unique authors, only 18 authors have contributed to more than one article.

Fig. 3 illustrates the distribution of published journal articles for the last 22 years. The results show an increasing trend in the adoption of machine learning methods to perform risk assessment. Other than the year 2012, the trend of published articles is increasing. Thirty journal articles were published in the year 2018, making it the most significant year for this emerging field.

Fig. 4 presents a Cholorpeth map with the number of articles published per country from the selected literature. The results show that the USA has the highest number of contributions, closely followed by China. Thirty-nine articles are published from USA and 30 published articles stem from China. South Korea is the third most contributing

Table 4
Distribution of selected articles amongst the top fifteen journal sources.

Journal source	Articles	Percentage of articles	Publications
Accident Analysis and Prevention	11	8.87%	(Farid et al., 2019, 2018; Goh et al., 2018; Kwon et al., 2015; Lavrenz et al., 2018; Marucci-Wellman et al., 2017a, 2017b; Siddiqui et al., 2012; Ketong Wang et al., 2016a, 2016b; Weng et al., 2015; Young et al., 2014; Zhu et al., 2018)
Safety Science	10	8.06%	(Alexander and Kelly, 2013; Ding et al., 2017; Jocelyn et al., 2018; Kaeeni et al., 2018; Kashani and Mohaymany, 2011; Mirabadi and Sharifian, 2010; Moura et al., 2017; Ouyang et al., 2018; Robinson et al., 2015; Sohn and Lee, 2003)
IEEE Transactions on Intelligent Transportation Systems	9	7.26%	(Aki et al., 2016; Brown, 2016; Liang et al., 2007; Ma et al., 2009; Salmane et al., 2015; Tango and Botta, 2013; Wang et al., 2010; Wang and Horn, 2018; Xiao et al., 2017)
Automation in Construction	5	4.03%	(Ding and Zhou, 2013; Kolar et al., 2018; Tixier et al., 2017, 2016b, 2016a)
Expert Systems with Applications	4	3.23%	(Bukharov and Bogolyubov, 2015; Cortez et al., 2018; Mistikoglu et al., 2015; Sugumaran et al., 2009)
Transportation Research Part C: Emerging Technologies	4	3.23%	(Ding et al., 2016; Ghofrani et al., 2018; Li et al., 2014; Pereira et al., 2013)
Journal of Safety Research	4	3.23%	(Chang and Chen, 2005; Chen et al., 2018; Tavakoli Kashani et al., 2014; Xu et al., 2018)
Sensors	3	2.42%	(Kim et al., 2017; Özdemir and Barshan, 2014; Wang and Niu, 2009)
Journal of Construction Engineering and Management	3	2.42%	(Cho et al., 2018; Wang et al., 2018; Zhao et al., 2018)
Reliability Engineering and System Safety	3	2.42%	(Fink et al., 2014; Rivas et al., 2011; Rocco and Zio, 2007)
Ocean Engineering	3	2.42%	(Rajasekaran et al., 2008; Xiang et al., 2017; Zhen et al., 2017)
Computers in Industry	2	1.61%	(Tanguy et al., 2016; Wu and Zhao, 2018)
Annals of Nuclear Energy	2	1.61%	(Ayo-Imoru and Cilliers, 2018; Lee et al., 2018)
Transportation Research Record	2	1.61%	(Pawar et al., 2015; Thakali et al., 2016)
Journal of Advanced Transportation	2	1.61%	(Hu et al., 2017; Saha et al., 2016)

Table 5
Top ten researchers applying machine learning for risk assessment.

Authors	Number of articles	Percentage
A.J.P. Tixier	3	2.42%
M.R. Hallowell	3	2.42%
Aty.M. Abdel	3	2.42%
B. Rajagopalan	3	2.42%
D. Bowman	3	2.42%
Z. Li	3	2.42%
A. Farid	2	1.61%
O.H. Kwon	2	1.61%
Y. Wang	2	1.61%
J. Lee	2	1.61%

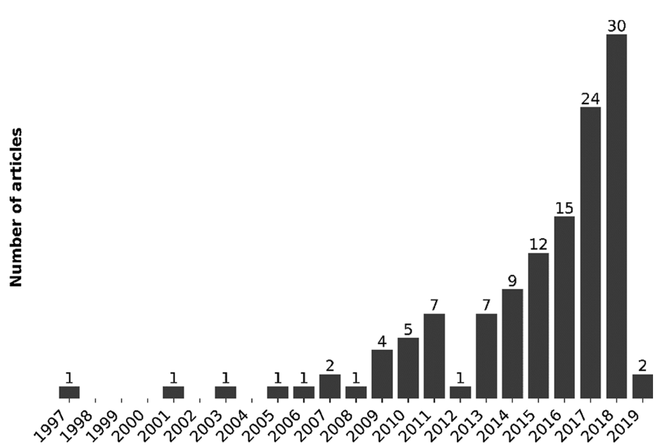

Fig. 3. Annual distribution of published journal articles focusing on the use of machine learning methods to perform risk assessment (literature search last updated in November 2018).

nation in this emerging field with 11 published articles.

Fig. 5 illustrates the types of journal articles reviewed. Of the 124 articles, 115 articles are original research articles and 9 are review articles. The results show that the review articles focus on the automotive, cyber-security, geology, railways, and road safety industry. Fig. 6 illustrates the type of journal. One hundred-five articles are published in subscription-based journals and 19 articles are published in open access journals.

3.3. Results obtained from reviewing the articles

The results in this subsection are founded on a structured effort to classify the 124 articles to a predetermined set of categories. These categories are classified for each article and results from this process are presented in this subsection.

Fig. 7 illustrates the distribution of different industries using machine learning methods to perform risk assessment. The results show that the automotive industry leads with 29 applications followed by the construction industry with 20 applications of using machine learning for risk assessments. In total, 17 different industries have explored machine learning applications for risk assessment. The review also found that 10 articles propose generic methods without limiting the methods to a specify industry. Therefore, these articles are classified into the "generic" category in Fig. 7.

A wide range of machine learning algorithms are being used to solve risk assessment-based problems. Fig. 8 illustrates the ten most frequently used learning algorithms to perform risk assessment. Applications of ANNs for risk assessment can be found in 36 different articles, closely followed by SVMs with 30 applications, and DTs with 18 applications. In total, 68 different machine learning methods are applied in the selected literature.

Fig. 9 illustrates the different data acquisition approaches used in the literature. Ninety-two articles use historically available data to develop the proposed machine learning based risk assessment models. Twenty-eight articles use real-time sensor data to feed into the proposed machine learning based risk assessment models as inputs. Only ten articles (review articles) describe using combination of historically available datasets and real-time sensor data.

The reviewed articles are also classified according to type of implementation. In total, 59 articles use case-studies to validate the proposed machine learning models. Thirty-three articles describe the development of a machine learning based risk assessment tool/application for real-world applications. Seventeen articles validate their machine learning models with aid of experimental setups. Six articles use a simulator environment to test the developed models. Fig. 10 illustrates

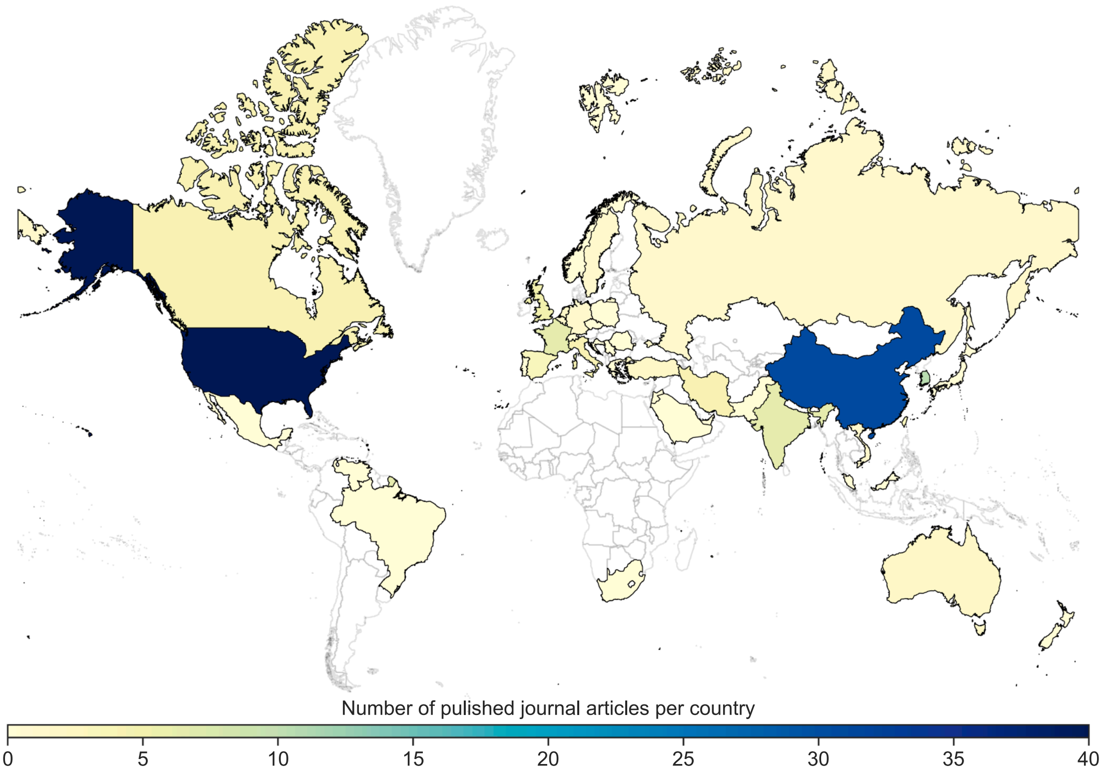

Fig. 4. Global distribution of published journal articles.

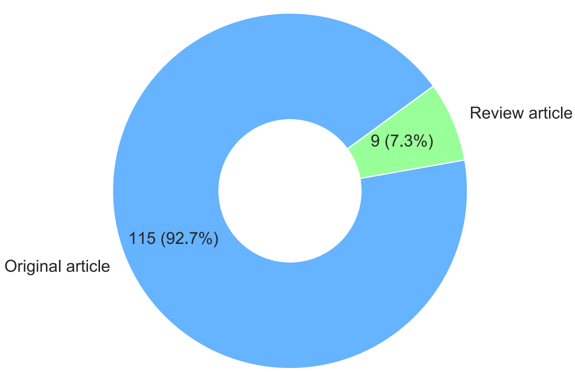

Fig. 5. Type of journal article.

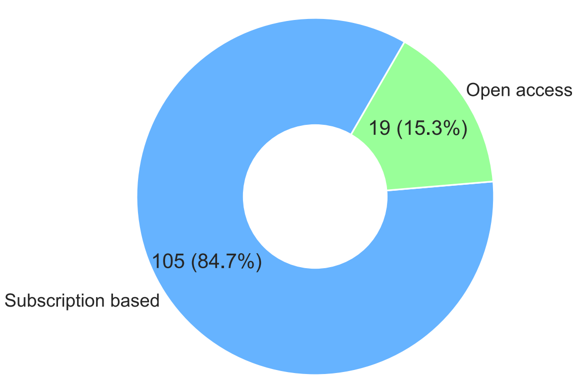

Fig. 6. Type of journal.

these results in a pie chart.

Table 6 extends the analysis scope from Fig. 10 by querying the article dataset with respect to the industry classification. The dark green shaded cells in Table 6 represents higher number of contributing

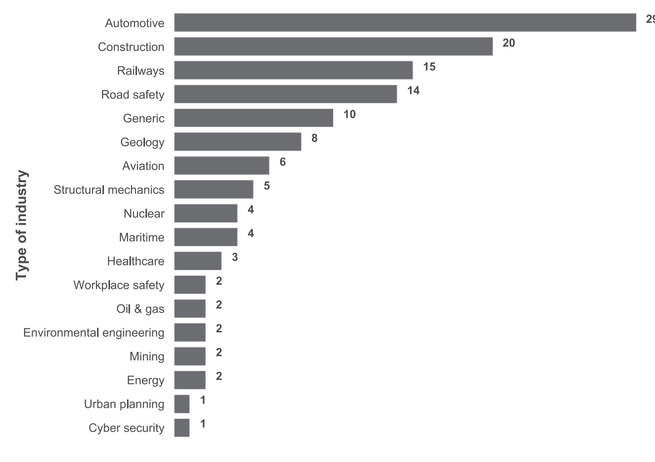

Fig. 7. Use of machine learning methods for risk assessment in different industries.

articles and the red shaded cells represent lower number of contributions. The results show that the articles related to the automotive industry frequently validate the models through real-world implementations. In addition, simulator-based implementation is only used by articles focusing on the automotive industry. On the other hand, the articles related to the construction industry validate using either case-studies, real-world implementation or experimental tests. It is to be noted that Table 6 is based on the industry wise classification of the articles as shown in Fig. 10. The contributions from some of the articles can be applicable in multiple industries and therefore, the total articles mentioned in Fig. 10 does not match with the column sum in Table 6.

The reviewed articles are classified according to their focus on different risk assessment phases, namely risk identification, risk analysis, and risk evaluation as described in Section 2.2.3 *Risk assessment phase*. Fig. 11 presents a Venn-diagram to represent the classifications of

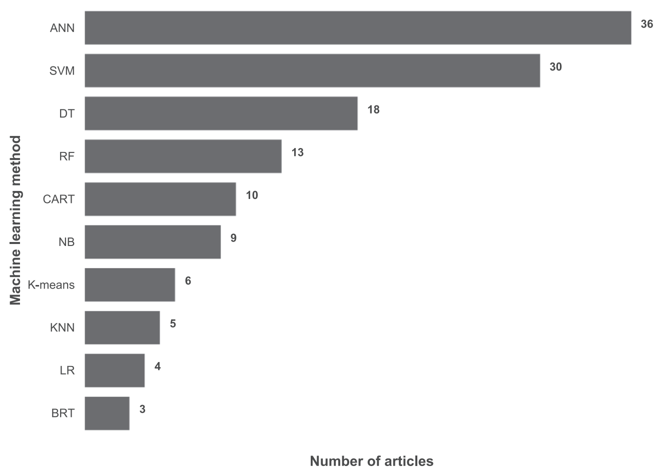

Fig. 8. Ten frequently used machine learning methods in risk assessment.

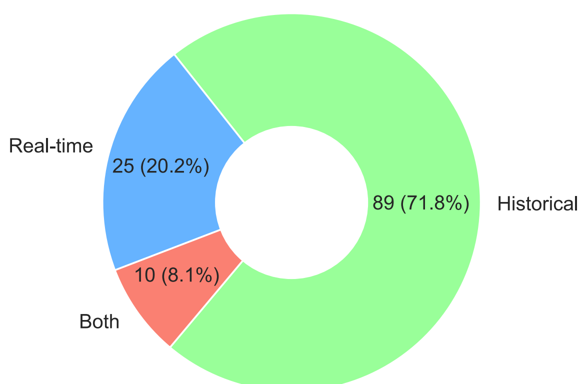

Fig. 9. Input data acquisition approaches utilized to build the model.

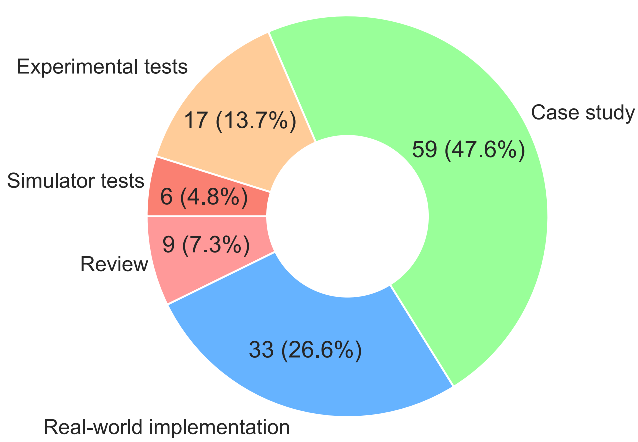

Fig. 10. Articles classified by type of implementation.

articles. Thirty articles focus on using machine learning to perform risk identification. Seven articles focus on using machine learning to perform risk analysis and only one article relates to use of machine learning to perform risk evaluation activities. Nineteen articles focus on all three phases of risk assessment.

An industry-wise segmentation of the different machine learning methods is presented in Table 7. The review of articles has also resulted in identifying the source of input data used in the literature to train the machine learning algorithms. Table 8 provides a collection of input data used to build machine learning models for risk assessment in different industries

4. Discussion

As shown in Fig. 8, ANNs are used more often in risk assessment than any other machine learning method in the selected literature. According to Bevilacqua et al. (2010) ANNs are advantageous because they use non-linear mathematical equations to develop meaningful relationships between input and output variables. Tu (1996) also suggests that ANNs require less formal statistical training to develop and they have the ability to detect all possible interactions between the input and output variables. These reasons may be the reason for the use of ANNs in the selected literature. However, ANNs also have disadvantages, which cannot be overlooked. ANNs are prone to overfitting i.e. the relationships between the inputs and outputs are generalized to a given set of data. According to Tu (1996), ANNs are also examples of “black box” methods and they cannot explicitly identify possible causal relationships between input and output variables. van Gulijk et al. (2018) suggest that the some “black box” methods in machine learning can make it difficult to trust the output of these methods.

It is challenging to avoid both type 1 and type 2 errors, which are encountered during the search process. Type 1 errors are the result of rejecting the true null hypothesis. On the contrary, type 2 errors occur due to failure of rejecting the false null hypothesis. In the context of this article, type 1 error resulted in search hits, which did not fit the filtering criteria. On the contrary, type 2 error occurred by failing to retrieve relevant articles which exist in the body of knowledge. The findings from the review process show that not all relevant papers were captured by the search engines of Scopus and Engineering Village. For example, Li et al. (2008, 2012) both use SVMs to classify and evaluate risk of road accidents. Unfortunately, these articles were not shortlisted during the literature searches by both Scopus and Engineering Village, resulting in a type 2 error. There may be two explanations for the occurrence of type 2 errors.

First, the terms used to describe the application of machine learning for risk assessment is not standardized. For example, different authors use different terminology. For example, Sohn and Lee (2003) use the term “data fusion” and Halim et al. (2016) use the term “artificial intelligence” to propose a model capable of predicting the severity of road accident. Terms, such *data mining, artificial intelligence, deep learning, visual analytics, ensemble techniques, data fusion* etc. are also used in the retrieved literature. Performing a literature review, which considers all possible keywords describing the vast field of machine learning is both time consuming and impractical. A second reason for the type 2 error may also be the lack of accurate *meta*-data information of the articles. This is evident in the article *meta*-data obtained on Engineering Village as it contains many missing or null values, which is inferior in quality compared to the *meta*-data information found on Scopus. For this reason, the article *meta*-data obtained on Engineering Village was improved by utilizing the *meta*-data information from Scopus. Doing this allowed for a uniform database, which aided the analysis phase of this review.

Section 3.1 and Fig. 9 show that most of the current research focuses on processing either historical or real-time numerical data. On the other hand, research on the use of textual data to aid risk assessment is comparatively uncommon. The reason for this may be linked to the nature in which the textual data is collected, usually by human narratives. On the contrary, numerical data can be collected with fewer human resource by the use of different sensors. It is to be noted that in both cases (numerical or textual), the processed data is always in a numerical form. For example, textual data can be converted into a bag-of-words where each word is given an index and frequency. This converts a textual array into a vector, which can be further used by the machine learning algorithms.

The findings from Fig. 11 show that although machine learning applications are suggested to aid risk assessment, the proposed methods are unevenly favoring risk identification and analysis phases of risk assessment. Surprisingly, only one application among the 124 articles

Table 6
Classification of articles with respect to type of implementation and type of industry.

Industry	Type of implementation				
	Case study	Real-world implementation	Experimental tests	Simulator tests	Review
Automotive	6	12	3	5	3
Aviation	4	1	1	0	0
Construction	10	6	4	0	0
Cyber security	0	0	0	0	1
Energy	2	0	0	0	0
Environmental engineering	1	1	0	0	0
Generic	5	0	1	0	4
Geology	3	3	2	0	0
Healthcare	2	0	1	0	0
Maritime	2	1	1	0	0
Mining	0	2	0	0	0
Nuclear	2	0	1	1	0
Oil & gas	1	0	1	0	0
Railways	9	4	1	0	1
Road safety	9	4	0	0	1
Structural mechanics	3	0	2	0	0
Urban planning	0	1	0	0	0
Workplace safety	2	0	0	0	0

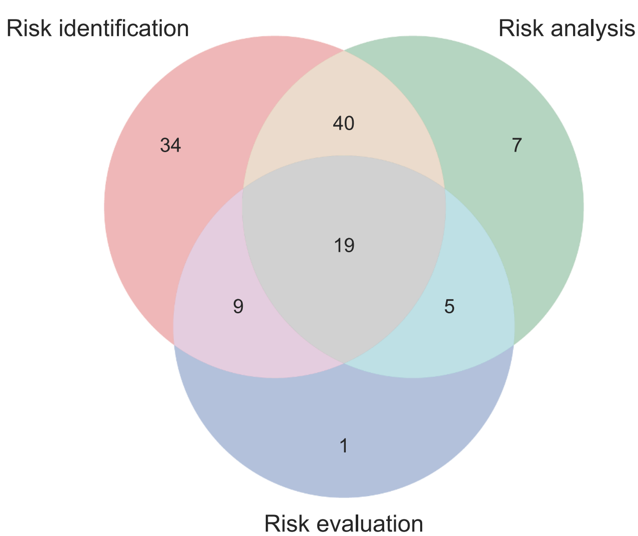

Fig. 11. Classification of articles with respect to the three risk assessment phases.

focus solely on risk evaluation (Curiel-Ramirez et al., 2018) in which the authors show how a vision-based system can aid in evaluating an ideal steering angle for an autonomous road vehicle. On the contrary, it can be argued that risk identification phase is easier when compared to applications needing risk analysis or evaluation. For example, Zhou et al. (2018) build a vision based machine learning algorithm to identify critical parts during the inspection of railway locomotives. There are no evident actions to be taken in this case other than identifying the object of interest.

Fig. 3 shows that the applications of machine learning in safety and risk engineering are increasing. Simultaneously, the challenges of using machine learning for risk assessment are also highlighted in the literature. For example, van Gulijk et al. (2018) suggest that safety scientists, will in the future, be confronted with machine learning methods and will have to evaluate the choice of the machine learning method. Therefore, safety scientists may also need to gain additional skills, such as data processing, to remain relevant in the age of real-time risk assessment. Halim et al. (2016) also highlight that there is a lack of benchmarked datasets in safety/risk engineering, which limits the comparison of research results with each other.

Another interesting finding is centered around the source of data used in the literature. Table 8 shows that the type of input data can be industry specific. This means that machine learning-based risk assessment utilize different data sources. This may signify that the machine learning model proposed by the authors may also be limited by the availability of data sources. For example, if road accident severity is considered, the developed machine learning model to predict the severity may be highly dependent on the input data source. If the data source is limited or of substandard quality, adopting/reusing the proposed method may not be feasible for other researchers. In short, the outcome of the machine learning model is highly dependent on the availability of input data source, which may hinder adoption, repeatability, or benchmarking of the proposed methods in the literature. By identifying and collecting all various sources of data in the selected literature, this review can benefit risk and safety researchers to identify suitable inputs for their applications by considering past applications. For example, if a risk assessment is being performed on an autonomous vehicle using a machine learning method, Table 8 can be referred to identify the type of input data used in existing literature.

5. Conclusions

Currently, a variety of machine learning methods are being used to aid phases of risk assessment, such as risk identification, risk analysis, and risk evaluation. Both historical and real-time data are being utilized to develop machine learning models capable of providing inputs to traditional risk assessment techniques. This paradigm shift is occurring across different industrial sectors, such as automotive, aviation, construction, railways etc.

This article has bridged the knowledge gap by performing a structured review of relevant literature focusing on the use of machine learning for risk assessment. The results show that 11 journal papers are

Table 7
Industry wise segmentation of machine learning methods used to aid risk assessment.

Industry	Machine learning method aiding risk assessment	Publications
Automotive	ANN	(Ma et al., 2009; Castro and Kim, 2016; Li et al., 2015; Curiel-Ramirez et al., 2018; Pereira et al., 2013; Taamneh et al., 2017; Sohn and Lee, 2003; Kim et al., 2017; Sayed and Eskandarian, 2001; Tango and Botta, 2013)
	SVM	(Ma et al., 2009; Jegadeeshwaran and Sugumaran, 2015; Kumtepe et al., 2016; Liang et al., 2007; Pereira et al., 2013; Kim et al., 2017; Tango and Botta, 2013)
	DT	(Castro and Kim, 2016; Pereira et al., 2013; Kwon et al., 2015; Taamneh et al., 2017; Sohn and Lee, 2003; Hu et al., 2017)
	CART	(Tavakoli Kashani et al., 2014; Chang and Chen, 2005; Kashani and Mohaymany, 2011; Siddiqui et al., 2012)
	NB	(Kwon et al., 2015; Liang et al., 2007; Taamneh et al., 2017; Aki et al., 2016)
	Logit model (Logistical regression)	(Chen et al., 2018; Tango and Botta, 2013)
	LR	(Li et al., 2015; Pereira et al., 2013)
	Probit model	(Weng et al., 2015)
	LDA	(Pereira et al., 2013)
	Radial basis function (RBF)	(Pereira et al., 2013)
	RF	(Yang et al., 2017)
	Instance based learning (IBL)	(Zhang and Yang, 1997)
	Predictive adaptive resonance theory (PART)	(Taamneh et al., 2017)
	Apriori	(Park et al., 2018)
	K-means	(Sohn and Lee, 2003)
	HMM	(Wang et al., 2010)
	Conditional random field (CRF)	(Wang et al., 2010)
	Review articles	(Lavrenz et al., 2018; Young et al., 2014; Halim et al., 2016)
Construction	ANN	(Li et al., 2006; Ding and Zhou, 2013; Butcher et al., 2014; Bevilacqua et al., 2010; Kolar et al., 2018; Goh et al., 2018)
	SVM	(Li et al., 2006; Goh et al., 2018; Wu and Zhao, 2018; Suárez Sánchez et al., 2011; Cho et al., 2018; Gui et al., 2017; Nath et al., 2018; Rivas et al., 2011)
	DT	(Bevilacqua et al., 2010; Goh et al., 2018; Hajakbari and Minaei-Bidgoli, 2014; Mistikoglu et al., 2015)
	RF	(Tixier et al., 2016a, 2016b; Goh et al., 2018; Zhou et al., 2019)
	SGTB	(Tixier et al., 2016b)
	Decision rules (DR)	(Rivas et al., 2011)
	Chi-square Automatic Interaction Detector (CHAID)	(Hajakbari and Minaei-Bidgoli, 2014; Mistikoglu et al., 2015)
	CART	(Hajakbari and Minaei-Bidgoli, 2014)
	C5.0	(Hajakbari and Minaei-Bidgoli, 2014; Mistikoglu et al., 2015)
	Quick, Unbiased and Efficient Statistical Tree (QUEST)	(Hajakbari and Minaei-Bidgoli, 2014)
	Negative binomial regression (NBR)	(Bevilacqua et al., 2010)
	NB	(Goh et al., 2018; Rivas et al., 2011)
	KNN	(Goh et al., 2018)
	K-means	(Hajakbari and Minaei-Bidgoli, 2014; Tixier et al., 2017)
	Iterative self-organization data analysis (ISODATA)	(Zhao et al., 2018)
	Equivalence class transformation (ECLAT)	(Wang et al., 2018)
	NLP	(Tixier et al., 2016a)
	PCA	(Tixier et al., 2017)
	Multiple correspondence analysis (MCA)	(Tixier et al., 2017)
	Agglomerative hierarchical clustering (AHC)	(Tixier et al., 2017)

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Table 7 (*continued*)

Industry	Machine learning method aiding risk assessment	Publications
Railways	ANN	(Feng et al., 2018; Kaeeni et al., 2018; Sohn and Lee, 2003; Jamshidi et al., 2017)
	SVM	(Li et al., 2014)
	DT	(Kaeeni et al., 2018; Sohn and Lee, 2003)
	NB	(Kaeeni et al., 2018)
	RF	(Brown, 2016)
	HMM	(Salmane et al., 2015)
	LDA	(Brown, 2016)
	Gradient boosting (GB)	(Brown, 2016)
	Associated rule analysis (ARA)	(Chen et al., 2015)
	Generalized rule induction (GRI)	(Mirabadi and Sharifian, 2010)
	Apriori	(Mirabadi and Sharifian, 2010; Ding et al., 2017)
	Continuous Association Rule Mining Algorithm (CARMA)	(Mirabadi and Sharifian, 2010)
	K-means	(Vagnoli and Remenyte-Prescott, 2018; Sohn and Lee, 2003)
	Multilayer neural network with multi-valued neurons (MLMVN)	(Fink et al., 2014)
	NLP	(van Gulijk et al., 2018)
	PCA	(Shi et al., 2015; Li et al., 2014)
	Review article	(Ghofrani et al., 2018)
Road safety	ANN	(Zhu et al., 2018; Shen et al., 2010)
	SVM	(Pawar et al., 2015)
	ARA	(Xu et al., 2018)
	RF	(Farid et al., 2019; Zhu et al., 2018; Saha et al., 2016)
	DT	(Tao et al., 2016)
	C4.5	(Tao et al., 2016)
	BRT	(Wang et al., 2016a, 2016b)
	Poisson regression (PR)	(Wang et al., 2016a, 2016b)
	NBR	(Farid et al., 2019; Wang et al., 2016a, 2016b)
	Regularized generalized linear model (RGLM)	(Wang et al., 2016a, 2016b)
	Least squares regression (LSR)	(Wang and Horn, 2018)
	KNN	(Farid et al., 2018)
	Gradient boosting logit model (GBLM)	(Ding et al., 2016)
	Kernel regression (KR)	(Thakali et al., 2016)
	Tobit	(Farid et al., 2019)
	Zero inflated negative binomial (ZiNB)	(Farid et al., 2019)
	Regression tree	(Farid et al., 2019)
	Boosting	(Farid et al., 2019)
	Poisson log normal (PLN)	(Farid et al., 2019)
	Review article	(Young et al., 2014)
Generic	ANN	(Bukharov and Bogolyubov, 2015; Cortez et al., 2018; Moura et al., 2017)
	SVM	(Anghel, 2009)
	DT	(Alexander and Kelly, 2013)
	LAD	(Jocelyn et al., 2018)
	Review articles	(Choi et al., 2017; Faouzi et al., 2011; Huang et al., 2018; Ouyang et al., 2018)
Geology	SVM	(Al-Anazi and Gates, 2010; Gnecco et al., 2017; Marjanović et al., 2011; Mojaddadi et al., 2017)
	Laplacian support vector machine (LapSVM)	(Gnecco et al., 2017)
	DT	(Marjanović et al., 2011; Wang and Niu, 2009)
	LR	(Marjanović et al., 2011)
	Relevance vector machine (RVM)	(Samui and Karthikeyan, 2013)
	RF	(Krkač et al., 2017)
	Ensemble approach	(Pham et al., 2017)

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Table 7 (*continued*)

Industry	Machine learning method aiding risk assessment	Publications
Aviation	ANN	(Tanguy et al., 2016)
	SVM	(Christopher et al., 2014; Tanguy et al., 2016; Puranik and Mavris, 2018)
	NLP	(Tanguy et al., 2016)
	DT	(Tanguy et al., 2016)
	KNN	(Tanguy et al., 2016)
	NB	(Tanguy et al., 2016) (Shi et al., 2017)
	LSA	(Robinson et al., 2015)
	LDA	(El Ghaoui et al., 2013)
	Sparse principal component analysis (SPCA)	(El Ghaoui et al., 2013)
	DBSCAN	(Puranik and Mavris, 2018)
	Hoeffding tree (VFDT)	(Shi et al., 2017)
	OzaBagADWIN (OBA)	(Shi et al., 2017)
Structural mechanics	ANN	(Salazar et al., 2015)
	SVM	(Chou et al., 2017)
	BRT	(Salazar et al., 2017; Salazar et al., 2015)
	CART	(Zhang et al., 2018; Chou et al., 2017)
	RF	(Salazar et al., 2015; Zhang et al., 2018)
	LR	(Chou et al., 2017)
	SVR	(Chou et al., 2017)
	DT	(Sugumaran et al., 2009)
Nuclear	ANN	(Ayo-Imoru and Cilliers, 2018; Lee et al., 2018)
	SVM	(Rocco and Zio, 2007)
	K-means	(Mandelli et al., 2018)
Maritime	DBSCAN	(Zhen et al., 2017; Xiao et al., 2017)
	ANN	(Rajasekaran et al., 2008)
	SVR	(Rajasekaran et al., 2008)
	Fuzzy neural network (FNN)	(Xiang et al., 2017)
	Kernel density estimation (KDE)	(Xiao et al., 2017)
Healthcare	ANN	(Wang et al., 2016a, 2016b; Özdemir and Barshan, 2014)
	KNN	(Özdemir and Barshan, 2014)
	Least squares method (LSM)	(Özdemir and Barshan, 2014)
	SVM	(Özdemir and Barshan, 2014)
	Bayesian decision making (BDM)	(Özdemir and Barshan, 2014)
	Dynamic time warping (DTW)	(Özdemir and Barshan, 2014)
Workplace safety	SVM	(Marucci-Wellman et al., 2017a, 2017b)
	Logistic regression	(Marucci-Wellman et al., 2017a, 2017b)
	NB	(Marucci-Wellman et al., 2017a, 2017b)
	LSA	(Robinson et al., 2015)
Oil & gas	FNN	(Xiang et al., 2017)
	CART	(Cheng et al., 2013)
Environmental engineering	CART	(Upton et al., 2017)
	K-means	(Shi and Zeng, 2014)
Mining	ANN	(Ribeiro e Sousa et al., 2017)
	CART	(Gernand, 2016)
	RF	(Gernand, 2016)
	DT	(Ribeiro e Sousa et al., 2017)
	KNN	(Ribeiro e Sousa et al., 2017)
	SVM	(Ribeiro e Sousa et al., 2017)
	NB	(Ribeiro e Sousa et al., 2017)
Energy	ANN	(Sun et al., 2017; Xu et al., 2011)
Urban planning	RBF	(Pyayt et al., 2011)
	Advanced K-means	(Pyayt et al., 2011)
Cyber security	Review article	(Elnaggar and Chakrabarty, 2018)

Table 8
Collection of input data used to build machine learning models for risk assessment in different industries.

Industry	Input data used in literature to train the machine learning models for risk assessment
Automotive	*'merging traffic data from a work zone in Singapore', 'textual accident description', 'car sensor data', 'steering angle', 'vehicle sensors', 'injury severity', 'gender', 'seatbelt', 'cause of crash', 'collision type', 'location type', 'lighting condition', 'weather conditions', 'road surface condition', 'occurrence', 'shoulder type', 'accident location', "driver's characteristics", 'environmental conditions', 'primary cause', 'injury levels of occupants', 'number of lanes', 'horizontal curvature', 'vertical grade', 'shoulder width', 'peak hour factors', 'traffic distribution over lanes', 'air pressure', 'temperature', 'humidity', 'precipitation', 'wind speed', 'cloudiness', 'accident data', 'roadway characteristics', 'trip production and attractions', 'simulator driving data', 'driver characteristics', 'accident records', 'historical traffic accident data', 'visual information', 'vehicle speed', 'engine speed', 'frontal stereo images', 'vehicle speed', 'steering-wheel angle', 'acceleration', 'braking activity', 'depth matrix of the radar and lidar', '360 vision images', 'measured angles in the xyz axes of the car', 'transient values of motion', 'vision', 'highway accident data', 'eye tracking data', 'vibration data', 'speed', 'acceleration', 'braking', 'steering', 'lateral lane position', 'weather', 'road condition', 'traffic light', 'pedestrian', 'buildings', 'vision', 'driving inputs', 'motorcycle accident data', 'vehicle specific accident data (STATS database)', 'environmental data', 'crash records', 'road design information', 'real-time traffic flow', 'weather', 'road surface condition', 'traffic accident records', 'express way work zone textual data', 'work description', 'Canadian crossing accident database'*
Construction	*'output from monte carlo simulations', 'textual injury reports', 'workplace hazard information', 'accident and incident data from interviews', 'incident reports', 'safety events', 'accident data', 'video', 'motion detection', 'predictions from mathematical models', 'results from field inspections', 'concrete thickness', 'employee status', 'employee company', 'occupation', 'occupation group', 'seniority', 'physical demands', 'work demands', 'body part discomfort', 'psychosocial needs', 'work rhythm', 'work extension', 'work life balance', 'workplace risk assessment', 'accident data', 'augmented images', 'survey data', 'strain data', 'finite element model', 'image', 'accident data from OSHA, 'injury reports', 'gyroscope data', 'accelerometer data', 'settlement stress', 'ground water level', 'lateral displacement', 'excavation depth'*
Railways	*'time to failure time-series', 'miles between failure time series', 'accident records', 'accident data', 'temperature', 'strain', 'vision', 'weight', 'impact', 'train accident data', 'vision', 'railway accident data', 'railway accident data', 'Iranian railway accident data', 'shape axel array data', 'video', 'number of passengers dispatched', 'passenger turnover volume', 'tonnage of freight dispatched', 'freight turnover volume', 'average daily output of freight locomotive', 'average daily number of car loadings', 'operating mileage', 'nitrogen monoxide', 'nitrogen dioxide', 'nitrogen oxides', 'particulate matters', 'carbon monoxide', 'carbon dioxide', 'temperature', 'humidity', 'Canadian crossing accident database'*
Road safety	*'crash data', 'distance between vehicles', 'signal timing', 'traffic information', 'surrounding drivers behavior', 'indicator data from SARTRE 3 report', 'intersection data', 'road traffic accident data from Anhui province', 'vehicle crash data', 'accident data', 'average annual daily traffic', 'segment length',, 'lane width', 'presence of paved shoulder', 'absence of paved shoulder', 'shoulder width', 'median width', 'crashes', 'road user behavior', 'vehicle condition', 'geometric characteristics', 'environmental conditions', 'crash records', 'video', 'express way work zone textual data', 'work description'*
Geology	*'well log data', 'longitude', 'latitude', 'distance to nearest stream', 'local surface curvature', 'the local contributing area', 'slope', 'elevation', 'slope angle', 'slope aspect', 'curvature', 'plan curvature', 'profile curvature', 'soil type', 'land cover rainfall', 'distance to lineaments', 'distance to roads', 'distance to rivers', 'liaments density', 'road density', 'river density', 'terrain data such as elevation', 'slope and profile curvature', 'cone resistance', 'maximum horizontal acceleration', 'satellite images', 'global navigation satellite system (GNNS) monitoring data', 'flood condition parameters'*
Aviation	*'aviation incident reports', 'aviation accident data', 'incident reports', 'flight-data records'*
Structural mechanics	*'vibration data', 'hydrostatic load', 'air temperature', 'rainfall', 'time', 'season', 'air temperature', 'reservoir level', 'daily rainfall', 'year', 'month', 'number of days from the first record', '4-story reinforced concrete building data', 'total chloride concentration', 'chloride binding', 'solution ph', 'dissolved oxygen', 'corrosion potential', 'pitting potential', 'pitting risk'*
Nuclear	*'time-dependent data', 'position', 'temperature', 'rcs pressure', 'rcs average temperature', 'sg feedwater flow', 'pressurizer level', 'charging flow', 'pressurizer heater power', 'temperature', 'pressure', 'level', 'pump state', 'tank state', 'valve state'*
Maritime	*'maritime ais data', 'pressure', 'wind velocity', 'wind direction', 'estimated astronomical tide', 'automatic identification system', 'waterway pattern', 'vessel motion behavior', 'underwater vehicle sensors'*
Healthcare	*'physiological signals', 'accelerometer reading', 'gyroscope reading', 'magnetometer reading'*
Workplace safety	*'textual accident narratives'*
Oil & gas	*'accident data', 'underwater vehicle sensors'*
Environmental engineering	*'process measurements', 'process parameters', 'source risk index', 'air risk index', 'water risk index', 'target vulnerability'*
Mining	*'mine inspection data sets', 'mine accident and injury data set', 'rockburst geometric characteristics', 'rockburst causes', 'rockburst consequences'*
Energy	*'generated operating points', 'voltage signals'*
Urban planning	*'dike measurements'*

published by the Journal of Accident Analysis and Prevention making it the most contributing journal source. Over 80% of the articles are published in subscription-based journals. Majority of the affiliated institutions in the articles are located in the United States of America closely followed by affiliations from Chinese and South Korean institutes. The automotive industry is leading the adoption of machine learning for risk assessment with over 20% of published articles and is closely followed by the construction industry with over 15% of published articles. Artificial neural networks (ANNs) are the most popular machine learning algorithm chosen to perform risk assessment followed by support vector machines (SVMs). More than 70% of the articles use historical datasets and more than 20% use real-time data to build the machine learning model. About half of the proposed methods use a case-study approach to implement the machine learning model and about one-fourth have implemented their proposed methods in a real-world setting. Risk identification is the most popular risk assessment phase to be aided by the proposed machine learning models in the literature.

Through the results of this review, it is evident that use of machine learning techniques for risk assessment is an emerging field of study given the increasing trend in annual publications. As more data is collected on different socio-technical systems, the adoption of machine learning methods may aid traditional risk assessment by providing data driven inputs. In the future, the industrial need for real-time risk assessment may also fuel the adoption of machine learning techniques. Moving forward, procedures to validate the use of machine learning in risk assessment also need to be addressed by the various safety regulatory bodies.

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