Abstract
Recent surveys have noted that the majority of bridges continue to serve for a prolonged period of time (+40 years) that far exceeds its intended operational lifespan. Given our limited resources to maintain and upkeep bridges, these structures become notoriously vulnerable to extreme events. Building upon the fact that bridges continue not to be specifically designed to withstand the adverse effects of fire, this study presents the development of a rapid, automated, and intelligent (RAI) approach that leverages machine learning to identify vulnerable bridges to fire hazard. This work also presents details on a comprehensive database comprising actual observations collected from 135 notable and international bridge fire incidents. This database was developed to train two machine learning techniques, deep learning and genetic algorithms, to quantify hidden patterns that govern the propensity of existing/new/historical bridges to undergo fire damage and/or fire-induced collapse via a multi-classification analysis. The proposed RAI approach also has the capability to pinpoint fire-vulnerable bridge components and to display its level of confidence in its predictions. As such, our approach can be of aid to bridge engineers and government officials (who may not be well-versed in fire design) with accuracy reaching 89.6%. This approach is implemented into a software (App) with optimized architecture and reduced computational complexity and hence is easily scalable and integratable into a user-friendly framework and
handheld devices. The outcome of this study shows that the RAI approach can be deployed to arrive at an instantaneous assessment of fire-vulnerable bridges.

**Keywords:** Bridges; Fire; Machine learning; Classification; Deep learning.

1. Introduction

Bridges are strategic transportation structures that offer commuters with a mean for ground transportation and facilitate supply chain operations. As such, bridges are expected to withstand day-to-day activities (i.e., traffic demands, etc.) and environmental conditions (wind, snow, etc.). Similarly, bridges are also equally expected to endure extreme load conditions as well such as impact and earthquake. Fortunately, bridge design codes provide guidance and provisions to enable engineers to properly designing bridges against the aforementioned actions [1,2]. However, there are still very limited provisions that cover the fire design of bridges [3]. In fact, the only standard that contains some guidelines to mitigate bridge fires is the National Fire Protection Association (NFPA) Report 502 [4]. Still, one should note that the NFPA 502 only lists general and qualitative recommendations that apply to bridges with long spans (greater than 300 m); which constitute a minute portion of total bridge population. In order to bridge this knowledge gap, a call for action is being fostered by various researchers [5–8].

Bridge fires have been recognized as a critical problem given the rapid urbanization and the fact that fires could break out anywhere and anytime due to natural causes (i.e., lightning, wildfires, etc.) or human interventions (vehicle collision, arson, terrorism, etc.) [9]. Bridge fires are associated with the burning of hydrocarbon fuels and unlimited ventilation, and hence these fires are classified with high intensity (e.g., temperatures rapidly reaching 800-1000°C within the first few minutes). Such fires release a significant amount of thermal energy and pressure, both of which
can adversely damage the integrity of a bridge infrastructure and develop thermally-induced forces that can trigger significant damage or collapse [6]. This, when combined with the fact that bridges lack fire protection measures or firefighting equipment, reflects the destructive nature of bridge fires [10,11]. Knowing that the majority of bridges are poorly maintained, with many showing signs of distress (e.g., cracking, exposed reinforcement, etc.) or being repaired with flammable fiber-reinforced polymers (FRP) systems, further amplifies the adverse effects of fire hazard [12]. While it is true that bridge fires may burn out quickly (whether due to firefighting or burning out of fuels), still such fires can induce large losses to physical properties of construction materials, and this may eventually lead to partial or complete collapse [13]. Fortunately, most bridge fires do not trigger a collapse but instead cause some level of damage. In such incidents, proper investigation, inspection, and maintenance of the damaged bridge are required to be undertaken by authorities. During this process, the bridge is either entirely or partially shut down as to serve a reduced traffic volume, which imposes substantial delays to traffic flow and supply chain operations [14].

Hence, identifying fire-vulnerable bridges can enable authorities and bridge engineers to take appropriate actions to help minimize the: (1) vulnerability of such bridges and (2) enhance the resilience of transportation networks. Given that there are more than 600,000 operational bridges in the United States infers that identifying fire-vulnerable bridges can both be hectic and time-consuming.

The open literature contains a few works that explored different solutions to identify vulnerable bridges to earthquake and flooding, but little research has examined the problem of bridge fires [15–18]. For instance, the authors have developed a fire-based importance factor approach similar
to that used for wind design in earlier works [19,20]. This importance factor is developed by assigning weightage factors to reflect upon: (1) the vulnerability of a bridge to fire hazard, (2) traffic usability of a bridge and (3) presence of any fire mitigation strategies. This importance factor approach was validated against a number of actual bridge fire incidents and, despite its iterative procedure, was shown to yield accurate predictions. In a similar manner, Peris-Sayol et al. [6] carried out a statistical analysis on 154 bridge fires. The outcome of their analysis shows that wooden bridges, as well as those built with steel I-girders, were shown to be most vulnerable to fire. As such, similar bridges were recognized to have high vulnerability to fire hazards. Finally, Gidaris et al. [21] proposed the use of multiple-hazard fragility and restoration models to identify vulnerable bridges within a transportation network. However, the same researchers also noted the lack of fragility models that can be applied to examine bridge fires.

This study hypothesizes that identifying fire-vulnerable bridges can be carried out with ease by leveraging a modern form of analysis that utilizes machine learning. As such, this paper tailors two machine learning techniques (namely: deep learning and genetic algorithm) to identify bridges’ vulnerability to fire hazards. These techniques are trained to analyze observations collected from 135 international bridge fires. The outcome of the presented analysis led to the development of a rapid, automated, and intelligent (RAI) approach that can be applied to identify vulnerable bridges to fire hazard, as well as estimate the expected degree of damage an existing, planned, or historical bridge could endure if exposed to a fire incident. The RAI approach is developed with an optimized architecture, and reduced computational complexity and hence is easily scalable and can be deployed to arrive at an instantaneous assessment of fire vulnerable bridges.
2. A Look into Recent Bridge Fires

Statistical studies that examine bridge fires were conducted by Wardhaua and Hadipriono [22] and Scheer [11]. These researchers reported that 3.2% and 4.9% of all bridges could experience some degree of damage due to fire throughout their service life, respectively. Thus, bridge fires can be classified under rare events [19,22]. Despite this small probability, Table 1 lists notable bridge fires that occurred due to varying causes. This table also shows the devastating effect of bridge fires in terms of structural damage and economic losses.

<table>
<thead>
<tr>
<th>Bridge location</th>
<th>Year</th>
<th>Cause of fire</th>
<th>Bridge type</th>
<th>Description of damage/collapse</th>
</tr>
</thead>
<tbody>
<tr>
<td>I-85, GA, USA</td>
<td>2017</td>
<td>Vandalism (burning of Polyvinyl chloride (PVC) pipes) that were stored under the bridge.</td>
<td>Concrete.</td>
<td>Major spalling and one span collapsed after 30 min of fire.</td>
</tr>
<tr>
<td>I-75, MI, USA</td>
<td>2015</td>
<td>Collision of a gasoline tanker carrying 9000 gallons.</td>
<td>Composite.</td>
<td>Concrete deck and steel girders were damaged.</td>
</tr>
<tr>
<td>Freeway 60, CA, USA</td>
<td>2011</td>
<td>Collision of a tanker truck carrying 128 m$^3$ of gasoline.</td>
<td>Prestressed concrete.</td>
<td>Concrete girders were significantly damaged.</td>
</tr>
</tbody>
</table>
Table 1 shows that most bridge fires break out due to spillage of highly flammable fuels or hydrocarbon chemicals (with low flash point) in the aftermath of the collision of fuel tankers. The same table also shows that bridge fires can occur due to natural causes (lightning strike), or manmade accidents (blowtorching, etc.). Thus, despite the common public perception that it is unlikely for a bridge to collapse as a result of a fire, as well as a low probability of fire break out in bridges, the fact of the matter is that intense fires can indeed trigger fire-induced collapse. It is worth noting that the New York state department of transportation reported that nearly three times more bridges have collapsed due to fire than earthquakes in a national survey covering different jurisdictions within the United States [23]. This survey emphasizes the importance of developing
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111 proper measures to mitigate bridge fires. To further illustrate the adverse impact of bridge fires, two incidents are described herein.

113 The first bridge fire broke out under the I-85 bridge near Atlanta, GA. The I-85 bridge was initially built in 1953 with ten prestressed concrete girders resting on reinforced concrete piers. This bridge was well maintained as it was refurbished in 1985 and scored a high sufficiency rating of 94.6% in 2015. On March 30, 2007, a fire broke out underneath the bridge due to the ignition of stored large Polyvinyl chloride (PVC) pipes. The burning of these PVCs has led to rapidly growing temperatures in the range of 900-1100°C. Thirty minutes into this fire, a 30.3 m long span collapsed, while adjacent piers and spans underwent significant fire-induced spalling damage. At the time of the fire, this bridge was estimated to serve 243,000 per day, and the losses arising from this incident were evaluated at $10 million.

122 The second bridge fire described here is one that broke out at the Wiehltal Bridge in 2004 in Germany. The Wiehltal steel bridge measures 705 m in length and 31 m in width. This fire ignited as a result of a collision between a speeding car and a fuel tanker that was transporting 8700 gallons of gasoline. This collision has pushed the fuel tanker through the bridge’s guardrail, letting it to fall from a height of 30 m, thus exploding and killing the driver. As a result of this explosion, intense heat was generated and reached temperatures of 1200°C [24]. This heat has severely damaged the unprotected steel bridge and caused it to deform over 60 m. While the bridge did not collapse, this fire has caused significant damages that required a 20 m × 31 m segment of the steel bridge to be replaced. The overall damage in the aftermath of this incident was estimated at €32 million, and it took three years to re-opened the bridge for traffic three years later. This incident is considered to be one of the most expensive accidents in Germany.
3. Development of Bridge Fire Database

To effectively adopt machine learning to identify vulnerable bridges to fire hazards, one must develop a proper database that covers various bridges and fires. Hence, a literature review was first carried out to document notable bridge fires. During this process, a challenge arises that is related to identifying key factors (from a fire-vulnerability point of view) as a mean to attain a proper database that will lead to developing an optimally designed machine learning architecture with low computing complexity. Thus, the survey prioritized to document key factors that were noted in recent works, recommendations of departments of transportations (DoTs), and from consultation with practicing engineers [3,6,7,19,20,25–29]. These recent works have identified a number of key factors that were then divided into three domains; physical features of bridges, traffic features served by the bridge, fire features of the incident, as well as the damage level imposed upon the bridge resulting from fire*. Overall, this survey led to collecting 135 international bridge fires with nine different features, each of which will further be described below.

3.1 Physical Features

The physical features that are identified to govern the vulnerability of bridges against fire hazard encompass: structural system and construction materials used in load bearing, span length and age of the bridge. A look into these features reveals that these are also the same characteristics that govern the structural performance of a bridge. For instance, typical “structural systems, S” in bridges can be grouped under cable-type (cable-stayed and suspension), girder-type (box or I-shaped), and arch/truss-like. Cable-type bridges are often designed to span over natural obstacles

* While the open literature contains much more bridge fires, the compiled database only opted to include bridges with full and reliable documentations on the aforementioned features.
or serve as landmarks, and hence these bridges have complicated construction and load pathing [27]. On the other hand, traditional types of bridges are associated with relatively short spans and easier design/construction. Figure 1 shows that the developed database contained 15 cable-type bridges, 81 girder-type bridges, and 39 arch/truss-like bridges. As expected, there is a smaller number of fires that occurred in cable-type bridges given that there is a smaller number of these bridges in a given bridge population.
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Fig. 1 Statistics of the developed database

(a) Structural systems

(b) Construction materials

(c) Span (listed in vertical axis) – represented in meter

(d) Age (range shown in brackets) – represented in years

(e) Geographic/historical importance

(f) Number of lanes

(g) Location of fire break out

(h) Fuel type

(i) Magnitude of damage
The aforenoted structural systems are often made from “construction materials, M” such as concrete, steel, or timber. While these three materials can satisfy design requirements at ambient conditions, each of these materials may still suffer from certain limitations under fire conditions. For example, steel and timber structural members are prone to fire damage due to the poor thermal properties of steel and the combustibility of timber. The same susceptibility may not be as apparent in concrete bridges (i.e., reinforced or pre-stressed concrete), especially those that utilize novel additives (steel and/or polypropylene fibers) to mitigate fire-induced spalling [30]. A blend between steel and concrete bridges results in a composite construction that capitalizes on the synergy between concrete and steel and hence achieves improved fire performance. Figure 1b shows that the collected database contains 38 concrete bridges (24 reinforced concrete and 18 pre-stressed concrete bridges), 41 steel bridges, 39 composite bridges, and 17 timber bridges†.

The “span, P” of a typical bridge is mainly governed by the presence of any natural obstructions (i.e., water bodies), selected structural system and material of construction, as well as expected traffic demands. Hence, the span of a bridge is directly linked to the bridge’s structural capacity and performance. The average span of all bridges collected as part of this database is 108 m, with a maximum of 737 m and a minimum of 5 m. The full distribution of spans in all bridges is shown in Fig. 1c. As can be seen, most of the bridges have spans that are shorter than 100 m, as typical of most highway bridges.

† Some modern bridges may solely use fiber-reinforced polymer (FRP) composites and/or special glasses as load bearing elements. Very limited works have examined these bridges and hence such bridges were not included in the developed database.
Bridges are open structures that are continuously exposed to weathering and environmental conditions. Hence, such structures experience continuous deterioration, whether arising from environmental factors (corrosion, humidity, etc.), loading factors (overstressing, fatigue), or extreme events (earthquakes, hurricanes, etc.). While most DoTs require bridges to be inspected regularly, the majority of bridges are not upgraded to current standards nor properly upkept due to the limited resources. To consider such effect, the “age, $A$” of a bridge is identified as a key character that falls under the physical features domain. The compiled database has an average age of 50.6 years (with standard deviation = 36.8 years). The same database also has a maximum and minimum age between 146 years and 1 year old, respectively.

### 3.2 Traffic Features

Two main features were found to be related to traffic demands in bridges; “geographical significance, $G$” as well as “number of lanes, $N$”. These features roughly represent the overall expected traffic flow, closeness of a given bridge to population concentration, and availability of nearby/alternative main routes. The geographical significance of bridges is grouped under three classes: rural, sub-urban and urban – following a previous work by the authors [20]. *Rural* bridges are those that serve small traffic and can be found in rural areas. *Sub-urban* bridges can be grouped under those that present landmarks to a specific region. Finally, *urban* bridges present bridges with high historical/national importance (i.e., Brooklyn Bridge, NY). Figure 1e shows that our database contains a uniform spread of bridges wherein: 46 bridges were classified under the rural category, and 44 and 45 bridges under sub-urban and urban categories, respectively. The number of lanes reflects the magnitude of allowed daily traffic and in way, a bridge’s traffic serving capacity. Figure 1f shows the distribution of bridges’ number of lanes wherein about half contains 1-3 lanes.
3.3 Fire Features

The magnitude of a bridge fire is governed by the type/size of available fuel and ventilation. While the latter can be assumed to be similar in all bridge fires, given that bridges are open structures, the type of fuel can vary from one incident to the other. As such, two features are identified to be of importance: “type of fuel, $T$” involved in the fire and “closeness of fire break out, $C$” to the bridge [31]. Three types of fuels were considered; those from vehicles in direct collision with other vehicles (i.e., gasoline/diesel), or those from fuel tanker/barge crashes (hydrocarbon fuels), and other types of flammables (i.e., stored materials, PVCs, wildfires, etc.) – see Fig. 1h. For simplicity, three locations for fire break out were considered herein; near/in the vicinity of the bridge, above the bridge, and under the bridge. Figure 1g shows that 4, 69 and 62 bridge fires belong to the aforementioned locations.

The reader should note that while the bridge fires collected in this study may not share a similar magnitude, still the harsh effects of a fire (whether by degrading material properties or imposing thermally-induced forces) share a similarity. In fact, such a factor may not be readily available as the size/intensity of a particular fire is not usually formally documented in a quantitative manner (i.e., with details on the exact magnitude of burned fuel, maximum temperatures reached, etc.) but instead is qualitatively described. As such, the magnitude of a bridge fire was not explicitly accounted for as a key feature.

While the above discussed nine features cover three domains, one can also argue that other features could also be considered (i.e., bridge rating, average daily traffic, last documented upkeep, etc.). However, many of such features were not explicitly added to the developed database due to the absence of evidence, especially in older or international bridges. On a more positive note, the
developed database can still be extended given that information on new features is provided. The methodology presented herein is scalable and can include additional dependent, as well as independent, features as shown in previous works [32–34].

3.4 Damage Magnitude

Contingent upon the fire incident, the magnitude of the damage the bridge experiences and any possible stress to the surrounding transportation network can vary. On the one hand, if a bridge does not undergo significant fire damage, then this bridge can be re-opened for traffic immediately.

On the other hand, major damage to a bridge is expected to be repaired. To enable timely repairs, traffic can be either reduced or detoured. Thus, there are three classes of “damage magnitude, $D$” that are to be considered herein; no/minor damage (does not necessitate shut down), significant damage (necessitates shut down), and collapse.

It should be noted that a criterion to evaluate the goodness of a database was proposed by Frank and Todeschini [35], who recommended data scientists to maintain a ratio of 3-5 between the number of observations and input parameters. In this work, this ratio was satisfied.

4. Description of Machine Learning Approach

The development of the proposed *RAI* machine learning approach and two computing techniques employed herein: deep learning (DL), and genetic algorithms (GA), are presented in this section.

4.1 General Approach

The proposed approach for identifying vulnerable bridges to fire hazards consists of two steps (see Fig. 2). First, a database (or several databases) on bridge fires is compiled. This database is then treated and processed via data structuring to handle outliers, missing data and/or apply feature transformation operations (i.e., aggregations, feature engineering, etc.). Typically, such operations
rely on domain knowledge, intuition, and data manipulation and hence can be lengthy and hectic to perform manually. Hence, feature transformation comes in handy, especially in large datasets of varying features. Then, suitable machine learning techniques are selected, and then these techniques are properly developed via a rigorous training and verification procedure. Such a procedure trains the selected techniques via analyzing actual bridge fires. As such, compiling a representative database that is uniformly and unbiasedly developed (such as that presented in Sec. 3.0) becomes of great importance. Once the selected techniques are adequately trained and validated, then these techniques are deployed. This deployment will entail analyzing new bridges (that were not used in the development stage) to evaluate their vulnerability against fire hazards.

Given the automated nature of the RAI approach, this approach can be easily integrated into bridge population (i.e., from national (Federal Highway Administration (FHWA)/National Bridge Inventory (NBI)) or regional (DoT-based) databases) to identify fire-vulnerable bridges with ease. RAI can also be deployed by design firms to analyze bridges being designed or retrofitted.
Once the vulnerable bridges are identified, then these bridges are further examined to pinpoint the cause(s) of this vulnerability. For example, a bridge could be vulnerable to a fire that would break out beneath the bridge as opposed to a fire breaking out on top of the bridge. In such a scenario, measures can be put in place to minimize this vulnerability, i.e., insulate bridge girders, provide fire-proof shields to piers, install fire deluge systems, etc. In another scenario, say a cable-type bridge is found to be vulnerable to top bridge fires, then cables can be coated with intumescent...
paints or fire-retardant materials etc. Other strategies could also be implemented, e.g., policy changes can be put in place to minimize fire risk. Such policies may include: prohibiting storing of flammable materials in the vicinity of vulnerable bridges, limit the speed of fuel tankers passing through vulnerable bridges, detour large fuel tankers away from vulnerable bridges etc. Once any of the above strategies are applied, the vulnerability of the bridge can be re-assessed in a more fine-tuned manner (via importance factor or finite element simulation, etc.) as described in previous publications [7,8,10,36,37]. For this purpose, load bearing members (i.e., girders) in a given bridge can be analyzed under representative thermal and mechanical loading effects to evaluate their fire resistance. If the fire resistance of girders is deemed inadequate, then such girders are re-configured by providing fire insulation. The modified bridge is then re-analyzed in an iterative procedure until an adequate insulation thickness (or any other possible solution for that matter) that allows the girders to achieve a satisfying fire performance is arrived at.

4.2 Deep Learning (DL)

The DL technique is inspired by the topology of the brain. In this topology, a number of layers are arranged in parallel (see Fig. 3). The first layer, also referred to as the input/receiver layer, receives the observations to be analyzed which in this case cover those representing structural, traffic, and fire features. These features are then processed to flow into subsequent layers. The next layers are called the hidden layers. The hidden layers contain processing units (neurons) that analyze the inputted features via specific weights (connections). During this processing procedure, the DL technique learns relevant patterns of how the input features and outcome of bridge fire converge and then maps such patterns through transformation operations. The training process continues until a pre-defined fitness metric(s) (i.e., number of iterations and/or error tolerance) between DL-
based predictions and observations of bridge fires (e.g., magnitude of damage observed from bridge fire incidents) is reached.

The DL network was developed herein using Keras library in Python [38]. First, we split the compiled database into two parts (80\% of the collected data were used for training purposes, and the remaining data were used for testing the DL and improve its accuracy). Via a trial-and-error process, we then used 5 hidden layers with 12, 10, 8, 5, and 3 neurons. In this DL network, the weight and bias function for inputs are both selected to satisfy the glorot_uniform initializer. This initializer draws samples from a uniform distribution within a range [-limit, limit]. The range employed herein is \( \sqrt{\frac{6}{\text{fan_in} + \text{fan_out}}} \) where \( \text{fan_in} \) is the number of input units in the weight tensor and \( \text{fan_out} \) is the number of output units in the weight tensor [38]. The activation functions for hidden layers were \( \text{relu}, \text{exponential}, \text{tanh}, \text{exponential} \) and \( \text{softmax} \), respectively\(^\dagger\).

Further, an optimization function is used to minimize the error. This function is \( \text{Adam} \) [39]. The optimization function is used to improve the internal parameters of the model such as weight and biased values. \( \text{Adam} \) is an adaptive learning rate method that is considered as a combination of \( \text{RMSprop} \) and \( \text{Stochastic Gradient Descent} \) with momentum. This method uses squared gradients to scale the learning rate like \( \text{RMSprop} \) and takes advantage of \( \text{Stochastic Gradient Descent} \) by using a moving average of a gradient \[39\]. For error or loss function, we define \( \text{categorical_crossentropy} \). It is a \( \text{softmax} \) activation plus cross-entropy loss since this is a multi-

\(^\dagger\text{Relu} \) is often used in the most neural conventional network or deep learning problems with function and derivative are both monotonic. Other functions are also used; \( \text{Exponential} \) which is \( \exp(x) \), \( \text{tanh} \) which is a hyperbolic tangent function. \( \text{Softmax} \) will calculate the probabilities of each target class over all possible target classes.
class problem. In order to improve accuracy, weight function needs to iterate several times. In this study, the epochs or iterations for the model is set to 29.

![DL network topology](image)

**Fig. 3** Representation of a typical DL network topology

**4.3 Genetic Algorithm (GA)**

Genetic algorithm is an evolutionary technique that utilizes supervised learning to arrive at relations (i.e., expressions) that represent a particular phenomenon (which in this case refers to the outcome of bridge fires). GA derives such relations by mimicking the natural selection process (survival of the fittest) [40]. GA starts by assigning an arbitrary population of expressions (or trees). Each tree houses mathematical symbols, functions, and operations – see Fig. 4. The analysis procedure starts by re-arranging such functions and operations in an attempt to arrive at an expression with high fitness (i.e., predictive capability). In this pursuit, GA employs refining operations that are also inspired by the natural selection process (i.e., reproduction, mutation etc.) to fine-tune a candidate expression. At the end of this analysis procedure, the fittest expression out of all other expressions is selected. Finally, the fittest tree is converted into “Karva-expression”
form that is easy to input into a spreadsheet-like program, i.e., Matlab, Python, etc. In this analysis, the notable works of [41, 42] (which were applied for classification problems and genetic programming modeling) and [43–45] (which tackled structural engineering problems) were used to identify suitable and commonly used mathematical, functional and genetic operators. An examination of such works shows that commonly adopted mathematical operators include addition, subtraction, multiplication, maximum, minimum, IF, and logical operators (such as and), and hence these were used herein. In addition, Step, Logistic, Trigonometric functions (i.e., TAN, COS) were also used as functions. For genetic operators, we used a mutation rate of 0.1, and a crossover rate of 0.85. In general, we deployed a population size of 1000, and a generation of 1200. The above was seen in very close to those used in the following references and hence proven effective herein. Further details on the development of a typical GA can be found elsewhere [32,41].

Fig. 4 Karva-expression for a tree representation of $\frac{x}{9y} + \frac{3}{z}$
5. Machine Learning Model Validation and Deployment

Now that the machine learning techniques are developed, these techniques are to be trained and validated. For this purpose, the database was arbitrarily arranged to minimize biases that might arise from a particular feature (say, structural system, etc.). After that, the database was used to train the model via a 10-fold cross-validation method in which the dataset is randomly split up into test and training subsets, which is further divided into 10 groups. This cross-validation method allows the model to train and be validated on multiple train-validation splits, thereby resulting in a high model performance with less overfitting [42]. The model is validated on one of the groups and trained using the other remaining 9 groups. This process is repeated 10 times until each unique group has been used as the validation subset. Finally, the model's performance is examined on the test data not seen by the model during training.

Table 2 shows the results of the model examination by means of the confusion matrix and fitness metrics for both DL and GA techniques when applied to the whole dataset. In this table, one can see that the DL model performed well in the Recall metric, which shows the ratio of correct positive predictions to the total positives examples but struggled in the case of Major damage. The same model performed well on the precision (which shows the ratio of correct positive predictions to the total predicted positives) front in identifying No/minor damage class. On the other hand, the GA model performed in a better sense than the former model by attaining improved and consistent metrics across all classes. In addition, it is worth noting that the overall accuracy for these techniques on the whole database is 70% and 89.6%, with a Kappa metric (which measures inter-rater reliability) reaching 0.494 and 0.832, respectively. It is worth noting that a Kappa metric score within 0.41–0.60, and 0.81–1.00 implies “moderate agreement” and “almost perfect
agreement”, respectively, as noted by Landis and Koch [43]. All of the aforementioned metrics reveal two observations, 1) both models seem to be of good standing, and 2) the accuracy of the GA algorithm over the DL technique. Overall, the listed metrics show that the proposed RAI approach can be used to classify fire damage in bridges with confidence (see Table 3).

Table 2 Confusion matrix of selected algorithms

<table>
<thead>
<tr>
<th></th>
<th>No/Minor</th>
<th>Major</th>
<th>Collapse</th>
<th>Precision (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DL</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No/Minor</td>
<td>63</td>
<td>15</td>
<td>5</td>
<td>75.9</td>
</tr>
<tr>
<td>Major</td>
<td>5</td>
<td>18</td>
<td>8</td>
<td>580</td>
</tr>
<tr>
<td>Collapse</td>
<td>2</td>
<td>5</td>
<td>14</td>
<td>66.7</td>
</tr>
<tr>
<td>Recall (%)</td>
<td>90.0</td>
<td>47.4</td>
<td>52.9</td>
<td></td>
</tr>
</tbody>
</table>

Table 3 GA-proposed expressions to evaluate expected damage to fire

<table>
<thead>
<tr>
<th>No.</th>
<th>Case</th>
<th>Derived expressions §</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Collapse</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>$\text{Collapse} = \text{step}(69.5 \times M + 7.6 \times S + i f(5.3 + 1.5 \times M \times C - 0.0062 \times P - 2.3 \times M - 3.07 \times C, \tan(218.24 + i f(0.39 \times N - 1.49, 0.39 \times N - 1.49, 0.85 \times M - 3.31)), 155.59 \times \max(1.08 \times T - 2.19, 1.79 \times C - 2.73)) - 146.45 - 0.103 \times A - 1.12 \times N - 1.98 \times P - 3.04 \times T - 6.49 \times G - 6.8 \times C)$</td>
</tr>
<tr>
<td>2</td>
<td>Major</td>
<td>$\text{MJ} = \text{logistic}(327.80 + i f(0.39 \times N - 1.49, 27.30 \times \cos(2.74 + 1.21 \times G - 3.08 \times P), 40.88 \times \min(1.21 \times G - 2.42, 0.398 \times N \times \tan(27.30 \times \cos(2.74 + 1.21 \times G - 3.08 \times P))) - 1.49 \times \tan(27.30 \times \cos(2.74 + 1.21 \times G - 3.08 \times P))) + 30 \times \min(0.85 \times M - 2.71, \min(0.39 \times N + \cos(2.74 + 1.21 \times G - 3.08 \times P) - 1.49), 1005.52 \times \cos(1005.52 \times \tan(0.39 \times N + \cos(2.74 + 1.21 \times G - 3.08 \times P) - 1.49)))) - 10.88 \times N \times \min(1.21 \times G - 2.42, 0.39 \times N \times \tan(27.30 \times \cos(2.74 + 1.21 \times G - 3.08 \times P))) - 0.21 \times P - 0.31 \times A - 6.71 \times N - 18.15 \times F - 18.25 \times M - 20.52 \times C - 21.42 \times G - 32.1 \times S)$</td>
</tr>
</tbody>
</table>

§All features were assigned an arbitrary numeric value such that:
- Structural systems: cable-stayed/suspension (1.0), truss/arch (2.0), box girders (3.0), and I-girders (4.0).
- Construction materials: prestressed concrete (1.0), reinforced concrete (2.0), and steel (4.0) and timber (5.0).
- Geographic significance: rural (1.0), sub-urban (2.0) and urban (3.0).
- Closeness of fire break out to bridge: top of bridge (1.0), under bridge (2.0), and in the vicinity of bridge (3.0).
- Fuel type: gasoline/diesel (1.0), hydrocarbons (2.0), and other flammables/storage (3.0).

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Since GA was found to have a superior predictivity, a sensitivity analysis was carried out on the proposed GA-derived expressions. In this analysis, the relative impact of each feature within each expression on the overall response to a bridge fire is examined and listed in Table 4. In this table, the % Positive refers to the likelihood that increasing a specific feature leads to an increase to the outcome (i.e., if % Positive = 75%, then 75% of the time an increase in a specific feature would lead to an increase in the outcome). The positive magnitude quantifies the amount of positive increase a specific feature can add to the outcome of the expression. Both, % Negative and negative magnitude are equal opposites to the above. A look into Table 4 shows that the main three features with the highest sensitivity (i.e., impact) are the span (P), age (A), and the number of lanes (N).

Table 4 Sensitivity analysis on the proposed expressions

<table>
<thead>
<tr>
<th>Exp.</th>
<th>Feature</th>
<th>Sensitivity</th>
<th>% Positive</th>
<th>Positive Magnitude</th>
<th>% Negative</th>
<th>Negative Magnitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>No/Minor damage</td>
<td>P</td>
<td>1.84</td>
<td>100%</td>
<td>1.84</td>
<td>0%</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>A</td>
<td>0.61</td>
<td>74%</td>
<td>0.61</td>
<td>26%</td>
<td>0.17</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>0.44</td>
<td>60%</td>
<td>0.49</td>
<td>40%</td>
<td>0.35</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>0.35</td>
<td>100%</td>
<td>0.35</td>
<td>0%</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>S</td>
<td>0.32</td>
<td>100%</td>
<td>0.32</td>
<td>0%</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>M</td>
<td>0.27</td>
<td>100%</td>
<td>0.27</td>
<td>0%</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>G</td>
<td>0.16</td>
<td>100%</td>
<td>0.16</td>
<td>0%</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>T</td>
<td>0.16</td>
<td>100%</td>
<td>0.16</td>
<td>0%</td>
<td>0</td>
</tr>
<tr>
<td>Major damage</td>
<td>P</td>
<td>44.2</td>
<td>45%</td>
<td>52.9</td>
<td>55%</td>
<td>37.21</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>0.62</td>
<td>20%</td>
<td>1.52</td>
<td>80%</td>
<td>0.39</td>
</tr>
<tr>
<td></td>
<td>S</td>
<td>0.40</td>
<td>0%</td>
<td>0</td>
<td>100%</td>
<td>0.40</td>
</tr>
<tr>
<td></td>
<td>M</td>
<td>0.31</td>
<td>0%</td>
<td>0</td>
<td>100%</td>
<td>0.30</td>
</tr>
<tr>
<td></td>
<td>T</td>
<td>0.24</td>
<td>0%</td>
<td>0</td>
<td>100%</td>
<td>0.24</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>0.22</td>
<td>0%</td>
<td>0</td>
<td>100%</td>
<td>0.22</td>
</tr>
<tr>
<td></td>
<td>A</td>
<td>0.21</td>
<td>0%</td>
<td>0</td>
<td>100%</td>
<td>0.21</td>
</tr>
</tbody>
</table>
A deeper look into the above three features shows interesting observations. For example, it is very likely for a bridge to experience a high degree of damage (or to possibly collapse) if such a bridge is made of steel or timber (e.g., an increase in $M$ from $1 \rightarrow 5$ has a $75\%$ likelihood of amplifying the outcome and leading to collapse). An equally exciting observation can also be seen in the case of $P$ and $N$, wherein an increase in these features (i.e., bridges with longer spans and/or a higher number of lanes) is expected to minimize the possibility of collapse. While the latter may seem counterintuitive, one should note that: (1) larger bridges are much more resilient and built to achieve higher levels of performance, and (2) very few large bridges ever collapse due to fire [11].

The above approach can now be deployed into a bridge master database (say from FHWA etc.) to identify vulnerable bridges. While the proposed approach was developed via complex machine learning analysis, still this framework was successfully employed into a simple Excel-like spreadsheet as well as software (App) that could be operated using a PC, tablet (i.e., iPad), or an iPhone (see Fig. 5). As such, users of $RAI$ approach do not need to have a background in coding nor to be in need of a specialized software (i.e., Matlab) or device to evaluate the vulnerability of bridges to fires.
The user may also opt to start the vulnerability analysis using hand-calculation. In this case, it would be optimal to start by applying the first expression to check whether the bridge will collapse or not. If the first expression returns a value of unity, then the bridge is expected to collapse, and if not, then the second and third expressions will be applied to estimate the magnitude of the damage the bridge will experience**. In any case, the user must note that the derived expressions may not be genuinely aesthetic nor compact, and this is attributed to the complex nature of bridge

** It is unlikely that the above expressions will agree on a specific outcome (i.e., all expressions yield an outcome of unity) for the same bridge. In any case, the designer might option to select the worst-case scenario outcome and/or try different approach such as bridge fire importance factor (which is based on weightage factors) [19] or finite element simulations [7].
fires these expressions reflect. In other words, mathematically representing the outcome of bridge
fires is hectic and requires a highly nonlinear form of expressions.

To further validate the proposed machine learning approach and software, the following three case
studies are carried out herein.

**Brooklyn Bridge**

The first case study covers a fire that broke out at the Brooklyn Bridge, NY. This fire resulted from
a fuel tanker collision with another vehicle on top of the bridge. Given the following features listed
below, it is clear that this bridge could undergo a minor degree of damage due to such fire. It
should be noted that the Brooklyn Bridge has undergone a number of similar fires over the past
few years [45,46]. The outcome of these fires has been documented to be of insignificant/minor
magnitude.

**Bridge features:**

**Physical features:**

- Structural systems, $S \rightarrow$ Suspension system = 1
- Construction materials, $M \rightarrow$ Steel = 4
- Span, $P \rightarrow$ 486 m
- Age, $A \rightarrow$ 143 years

**Traffic features:**

- Geographical significance, $G \rightarrow$ Urban = 3
- Number of lanes, $N \rightarrow$ 6 lanes

**Fire features:**

- Closeness of fire break out, $C \rightarrow$ Above bridge = 1
Type of fuel, $T \rightarrow$ Hydrocarbon fuels = 2

**Step 2:** Deploy machine learning techniques:

*Based on DL tool*

Predicts the bridge will experience no/minor damage.

*Based on GA-proposed expressions:*

$\text{Collapse} = \text{step}(69.5 \times 4 + 7.6 \times 1 + if(5.3 + 1.5 \times 4 \times 1 - 0.0062 \times 486 - 2.3 \times 4 - 3.07 \times 1, \tan(218.24 + if(0.39 \times 6 - 1.49, 0.39 \times 6 - 1.49, 0.85 \times 4 - 3.31)), 155.59 \times \max(1.08 \times 2 - 2.19, 1.79 \times 1 - 2.73)) - 146.45 - 0.103 \times 143 - 1.12 \times 6 - 1.98 \times 486 - 3.04 \times 2 - 6.49 \times 3 - 6.8 \times C) = 0.0$ (the bridge is not expected to collapse $\rightarrow$ check for expressions 2 and 3).

$\text{No/MN} = \text{step}(17.57 \times 4 + 3.03 \times 1 + \tan(if(0.006 \times 486 - 0.67, -1.53, if(1.37 \times \text{and}(0.31 - 0.0062 \times 486, 1.8 \times 1 - 2.73) - 0.36 - 0.027 \times 143 \times \text{and}(0.31 - 0.006 \times 486, 1.79 \times 1 - 2.73), 1.79 \times 1 + 0.91 \times 1 + 0.0028 \times 486 - 5.74, if(0.39 \times 6 - 1.49, -1.52, if(1.08 - 0.027 \times 143, 1.79 \times 1 + 0.0061 \times 486 - 3.39, -1.525))) - 39.98 - 0.024 \times 486 - 0.047 \times 143 - 0.19 \times 6 - 0.53 \times 2 - 3.12 \times 1 - 6.54 \times 3) = 1.0$ (this bridge is likely to undergo no/minor damage).

**Golden Gate Bridge**

The second case study covers a bridge fire that broke out in a traffic jam upon the Golden Gate Bridge, CA [47]. This fire resulted from a car collision. The bridge was reported to undergo a minor degree of damage due to such fire.

**Bridge features:**

Physical features:

Structural systems, $S \rightarrow$ Suspension system = 1

Construction materials, $M \rightarrow$ Steel = 4

Span, $P \rightarrow$ 1280 m
Age, \( A \rightarrow 82 \) years

Traffic features:

Geographical significance, \( G \rightarrow \text{Urban} = 3 \)

Number of lanes, \( N \rightarrow 6 \) lanes

Fire features:

Closeness of fire break out, \( C \rightarrow \text{Above bridge} = 1 \) (since the bridge crosses The Golden Gate strait and has a 67.1 m clearance above sea level).

Type of fuel, \( T \rightarrow \text{Hydrocarbon fuels} = 2 \)

Step 2: Deploy machine learning techniques:

**Based on DL tool**

Predicts the bridge will experience no/minor damage.

**Based on GA-proposed expressions:**

\[
\text{Collapse} = \text{step}(69.5 \times 4 + 7.6 \times 1 + \text{if}(5.3 + 1.5 \times 4 \times 1 - 0.0062 \times 1280 - 2.3 \times 4 - 3.07 \times 1, \tan(218.24 + \text{if}(0.39 \times 6 - 1.49, 0.39 \times 6 - 1.49, 0.85 \times 4 - 3.31)), 155.59 \times \max(1.08 \times 2 - 2.19, 1.79 \times 1 - 2.73)) - 146.45 - 0.103 \times 82 - 1.12 \times 6 - 1.98 \times 1280 - 3.04 \times 2 - 6.49 \times 3 - 6.8 \times 1) = 0.0 \] the bridge is not expected to collapse \( \rightarrow \) check for expressions 2 and 3).

\[
\text{No/MN} = \text{step}(17.57 \times 4 + 3.03 \times 1 + \tan(\text{if}(0.006 \times 1280 - 0.67, -1.53, \text{if}(1.37 \times \max(0.31 - 0.0062 \times 1280, 1.8 \times 1 - 2.73) - 0.36 - 0.027 \times 82 \times \max(0.31 - 0.006 \times 1280, 1.79 \times 1 - 2.73), 1.79 \times 1 + 0.91 \times 1 + 0.0028 \times 1280 - 5.74, \text{if}(0.39 \times 6 - 1.49, -1.52, \text{if}(1.08 - 0.027 \times 82, 1.79 \times 1 + 0.0061 \times 1280 - 3.39, -1.525)))) - 39.98 - 0.024 \times 1280 - 0.047 \times 82 - 0.19 \times 6 - 0.53 \times 2 - 3.12 \times 1 - 6.54 \times 3) = 1.0 \] this bridge is likely to undergo no/minor damage).
The first case study covers the bridge fire that caused the collapse of MacArthur Maze in Oakland, CA in 2007. This fire broke out once a fuel tanker carrying 8450 gallons crashed under the MacArthur Maze interchange. This crash ignited the highly flammable fuel, which generated intense heat and temperatures exceeding 1000°C. The intense heat severely degraded the strength and stiffness of steel girders in this composite bridge, which had no fireproofing. As a result, significant fire-induced forces were developed in the weakened girders. After 22 minutes of the fire, the bridge collapsed. This collapse resulted in damages that were estimated at $9 million and shut down traffic in all three lanes causing significant detours.

**Bridge features:**

**Physical features:**

- Structural systems, $S \rightarrow$ 1-girders = 4
- Materials of construction, $M \rightarrow$ Composite (steel and concrete) = 3
- Span, $P \rightarrow$ 24.5 m
- Age, $A \rightarrow$ 37 years

**Traffic features:**

- Geographical significance, $G \rightarrow$ Urban = 3
- Number of lanes, $N \rightarrow$ 6 lanes

**Fire features:**

- Closeness of fire break out, $C \rightarrow$ Under bridge = 2
- Type of fuel, $T \rightarrow$ Hydrocarbon fuels = 2
Step 2: Deploy machine learning techniques:

Based on DL tool

Predicts the bridge will experience collapse.

Based on GA-proposed expressions:

\[
\text{Collapse} = \text{step} \left( 69.5 \times 3 + 7.6 \times 4 + \text{if} \left( 5.3 + 1.5 \times 3 \times 2 - 0.0062 \times 24.5 - 2.3 \times 3 - 3.07 \times \\
2, \tan(218.24 + \text{if} \left( 0.39 \times 6 - 1.49, 0.39 \times 6 - 1.49, 0.85 \times 3 - 3.31 \right), 155.59 \times \max(1.08 \times 2 - \\
2.19, 1.79 \times 2 - 2.73) \right) - 146.45 - 0.103 \times 37 - 1.12 \times 6 - 1.98 \times 24.5 - 3.04 \times 2 - 6.49 \times 3 - \\
6.8 \times 2 \right) = 1.0 \text{ (the bridge is expected to collapse – a check for expressions 1 and 2 returns a “0” value).}
\]

It is worth mentioning that the above bridge is expected not to collapse (in this particular bridge fire) has it been designed with reinforced concrete girders as opposed to a composite system with steel I-girders. This infers the vulnerability of uninsulated steel girders to fire hazards. Other observations can also be arrived at by examining variations in expression no. 3.

This outcome of this example shows that predictions from DL and GA may not always agree with documentation and observations from the actual incident, given their accuracy, which falls short of 100%. In this scenario, a designer may opt to select the worst-case scenario to be on the conservative side or perhaps s/he may option to undertake a much detailed analysis, say via complex FE analysis. Overall, the RAI approach is being improved to adopt ensemble (multi-algorithms) machine learning technique to allow “majority voting”. In this technique, a fire vulnerability class will be assigned to a given bridge based on common class predictions from different algorithms.
6. Considerations for Future Works

The proposed RAI machine learning approach seems to truly capture patterns of bridge fires and how such fires may adversely affect the integrity of bridges, and in some instances, may result in significant damage and/or collapse. This work could be regarded as a first step towards realizing a modern and automated identification of fire-vulnerable bridges. Still, the reader is to remember that a few burning issues continue to arise. For example, machine learning tools are best suited where there is a large number of observations. However, observations on bridge fires are: 1) very limited, 2) rarely documented or easily accessible, and 3) lack completeness in reporting common features such as (fire intensity, fire spread, quantitative damage assessment etc.). The above could also arise issues with regard to reliability, scalability, and public acceptance. Fortunately, these challenges will be overcome in future works [48–51].

For now, the presented approach can still be confidently applied as a raw assessment tool that has the capability to offer designers with qualitative insights into how to mitigate extensive fire damage in bridges [32]. For example, the proposed tool can be applied during the early stage of the design of a new bridge to assess its vulnerability to fire (given that we still lack codal guidance on design a bridge for fire hazards). As such, the proposed tool could identify possible fire-related weaknesses such as that with regard to selecting a structural system or construction materials, etc. Arriving at such information during the design stage could be both of merit and cost-effective. Overall, the proposed approach can be considered as an “expert system” that can supplement current design procedures and may in fact compensate for the deficiency that a number of bridge engineers might suffer from when it comes to fire hazards.
A promising and attractive feature of machine learning approaches is their ability to self-improve with time and with the addition of new observations. As such, the proposed RAI approach could theoretically undergo a more rigorous validation and calibration process before being formally adopted into practice. Furthermore, effort should be made to develop machine learning tools that can quantitatively identify the magnitude of bridge damage to various extreme events as well as pinpoint how load bearing members will fail, and estimate expected cost of bridge restoration, indirect cost of shut down/supply chain operations, etc. Additional considerations worthy of note are those related to developing bug-free, user-friendly and aesthetic packages to allow scalable and easily deployable frameworks. Such a tool can be fostered by a government-based organization (i.e., DoTs) and can be linked to a computing cloud. Considerations with regard to security and wrongful use need to be addressed. Finally, the use of active learning techniques or reinforcement learning can help arrive at more optimal architecture of DL models, such as that developed herein, and hence future works are invited to tackle such research areas.

7. Conclusions

This paper presents the development of a rapid, automated, and intelligent (RAI) approach that leverages two machine learning algorithms DL and GA, to identify fire-vulnerable bridges. By examining 135 actual bridge fire incidents, the proposed approach has achieved an accuracy ranging between 70-89.6%. The proposed RAI approach also can quantitatively display its level of confidence in its predictions which can become handy to bridge engineers and government officials. This approach is implemented into freely available software (App) with optimized architecture and is easily scalable into a user-friendly framework and handheld devices. The following conclusions can also be drawn from this work:
• Recent years have noted a rise in bridge fires. Such fire incidents have led to damages and, in some cases, collapse. These incidents clearly show the vulnerability of bridges to fire hazards, given that these structures are not properly designed to withstand hazards.

• Machine learning can be successfully applied to develop bridge assessment tools that can identify vulnerable bridges to fire hazard. These techniques can be specifically tailored to account for varying features such as those related to physical characteristics, traffic demands, fire intensity, etc., and can achieve 82.9-89.6% accuracy as noted in this study.

• The RAI approach has optimized architecture and reduced computational complexity and hence is easily scalable and integratable into a user-friendly framework. This approach can be deployed to arrive at an instantaneous assessment of fire vulnerable bridges.

• Future machine learning techniques can be enhanced given the addition of accurately documented observations on bridge fires. The same techniques are expected to be able to arrive at a quantitative assessment of expected damage and associated economic losses etc.

8. Acknowledgment

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588 detailing rules, 2005.


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