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Autonomous Fire Resistance Evaluation

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Abstract

The structural fire engineering community has been slowly evolving over the past few decades. While we continue to favor a classical stand towards evaluating fire resistance of structures through fire experimentations, a movement towards developing numerical assessment tools is on the rise. A close examination of notable works shows that the majority of these tools continue to have limited scalability, lack standardization and thorough validation. Perhaps two of the main challenges of adopting such tools can be summed by their need for collecting true representation of response parameters (e.g. temperature-dependent material properties etc.), and necessity to carry out resource-intensive two-stage thermo-structural analysis. In order to overcome such challenges, and in pursuit of modernizing fire resistance evaluation, this paper introduces a new generation of fire-based evaluation tools that capitalize on perception rather than imitation. More specifically, this paper explores how automation and cognition (A&C), realized through machine learning (ML), can be applied to comprehend structural behavior under fire conditions. To achieve this goal, genetic programing (GP) and computer vision (CV) are utilized to assess fire response of structural members. The outcome of this study demonstrates that A&C can accurately evaluate fire resistance and identify damage/spalling magnitude in RC structures; thus, paving the way to realize autonomous fire-based evaluation and inspection.

Keywords: Fire resistance; Automation; Cognition; Machine learning.

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1.0 Introduction

Fire resistance of structural members and/or assemblies is often evaluated through a specialized testing procedure in which a representative specimen (say a beam) is loaded with a portion of its capacity (e.g. 50% of moment capacity) while simultaneously being subjected to a predetermined temperature-time conditions (i.e. standard fire curve such as ASTM E119). During this testing procedure, both thermal (temperature rise and propagation) as well as structural (mid-span deflection) responses are monitored until failure of the beam. In this scenario, failure could occur due to exceeding a/multi failure criteria; such as a certain level of deflection and/or rate of deflection (ASTM, 2016). At this point in time, the test is terminated and the duration it took the beam to fail is referred to as fire resistance[†]. An in-depth examination of the history of this evaluation procedure shows that standard fire testing not only remains virtually the same for the past 100 years, but is also costly, applicable to certain elemental configurations, and involves specialized testing facilities/certified personnel (Kodur et al., 2012; Wang et al., 2012).

With the intention of overcoming many of the shortcomings of standard fire testing procedure and in pursuit of facilitating a smooth transition towards performance-based solutions, our community started to favor development of advanced numerical approaches to evaluate fire resistance of structural members (Buchanan, 1994; Mostafaei, 2013). These approaches apply rational engineering principles to evaluate fire resistance of structural members and components. Advanced calculation methods often comprise of highly nonlinear finite element (FE) (or finite

[†]A more in-depth description on fire resistance testing procedure as well as documentation of failure time is avoided herein for brevity but can be found elsewhere (ASTM, 2016).

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difference (FD)) numerical models that can be developed using commercial or open source software.

While such methods have managed to advance and accelerate fire resistance evaluation procedure and, in a way, allowed its ease of application and convenience, the fact that the development of advanced models can only be carried out in specialized simulation environment (software – which implies the need for adequate licensing, training and availability of high computational/processing capacity) and continues to require input of large number of parameters (i.e. temperature-dependent material properties, realistic boundary conditions etc.), limits the complete adoption of these methods into practical situations. Perhaps the main challenges that remain to-be-resolved are the lack of a well-established validation and verification procedure and unified/agreed upon simulation practice (i.e. convergence/tolerance criteria, pre/post processing data extraction etc.). While it is interesting to note that some of the early works utilizing advanced calculation methods dates back to 1990s (Lie and Chabot, 1990; Huang et al., 1996), it is also surprising to report that recent works continue to report similar limitations and challenges as those noted by aforementioned pioneering studies (Hawileh et al., 2009; Naser, 2016). This showcases the merit of gravitating towards a more modern perspective.

It is of no doubt that contemporary developments in data analytics and computer science have led to significant advancements within engineering and physical disciplines. With the help of machine learning (ML), opportunities continue to arise as the intersection of data mining and engineering observations converges into new insights that further our knowledge on unique and seemingly complex phenomena (Jordan and Mitchell, 2015). In fact, the current literature displays

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the outcome of successful studies that adopted ML-based technologies in various civil engineering sub-fields i.e. transportation (Seitllari, 2014), damage identification (Huang et al., 2015), material sciences (Ghodrati and Aghaei, 2017), and design optimization (Adeli and Karim, 1997) etc. Unfortunately, the same review of literature also shows that the use of ML into structural fire engineering problems over the past three decades is alarmingly deficient (Adeli, 2001; Naser, 2019c). In reality, the bulk of the available studies in this field continue to apply outdated forms of ML towards simple construction/structural engineering-related phenomena (Dobrzański et al., 2005; Hoła and Schabowicz, 2005; Lee 2003; Naser et al., 2012; Trtnik et al., 2009).

This can be attributed to the fact that adopting ML as a solution strategy requires the availability of comprehensive datasets – preferably in the form of experimental observations collected from fire tests. Due to complexities arising from limited availability of testing facilities, together with severe nature of fire testing (e.g. instrumentation survivability, reliability of testing method, scarce number of tested specimens etc.) and confidentiality of industry-driven testing, it is not surprising that fewer fire testing programs have been carried out as oppose to those investigating other loading effects (i.e. earthquake, wind etc.) (Buchanan and Abu, 2017; Lie, 1992). While this explains the righteous notion of the limited number of suitable data points (i.e. outcome of fire tests) – a known fact in this research area, a positive look into the above discussion shows the potential of assembling available and representative datapoints into proper databases (Naser 2019a).

With the hope of bridging this knowledge gap, this work presents a novel approach that capitalizes on modern concepts; namely automation and cognition (A&C), to comprehend

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structural behavior during or in the aftermath of a fire incident. Rather than applying traditional ML techniques, contemporary ML-based technologies i.e. genetic programing (GP) and computer vision (CV) are examined herein. More specifically, this work applies GP and CV to establish ML-based approaches that can be utilized to autonomously assess fire resistance and damage mechanisms in a variety of structural members. Of interest to this work is to develop GP-derived expressions to evaluate fire resistance of reinforced concrete (RC) beams and columns under fire conditions as well as to estimate residual capacity of these structural members post-exposure to fire. In addition to developing the aforementioned expressions, this work also applies CV to detect another phenomenon; namely, the severity of fire-induced spalling in RC members. The presented results show the adequacy and potential of these two methodologies to serve as intelligent tools that can accurately evaluate fire resistance and identify damage mechanisms in structures. These results also show the merit of adopting similar technologies to realize autonomous and self-diagnosing structures that can facilitate safe post-fire inspections and timely repairs.

2.0 An Overview to Machine Learning (ML), Genetic Programing (GP), and Computer Vision (CV)

Machine learning is a subset of artificial intelligence (AI) and primarily focuses on the ability of machines to receive a set of data, comprehend this data and then learn and identify its key features in order to arrive at a suitable representation that best demonstrates the phenomenon embodied within the dataset (Sayad et al., 2019). Machine learning can come in handy in practical scenarios, where mathematical or conventional modelling approaches become obsolete as a result of limitation of precise reasoning in modeling multi-dimensional problems or uncertainties arising from the complexity of a given phenomenon etc. In order to overcome these limitations, ML uses

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a combination of novel techniques; such as artificial neural networks (ANNs), evolutionary computing (EC) etc., that mimics human learning process into the area of computing. ML can be broadly grouped into supervised, unsupervised and semi-supervised learning (Bishop, 2006). It should be noted that a brief review of ML methods can be found in more details in the following references (Caruana and Niculescu-Mizil, 2006; Chapelle et al., 2009).

2.1 Genetic programing (GP)

Genetic programing, developed in 1950s (Friedberg, 1958), improved in 1980s (Cramer, 1985) and popularized in early 1990s (Koza, 1992), is often considered an extension to genetic algorithms (GAs). GP is a supervised ML algorithm that follows principles of the Darwinian evolutionary theory to generate mathematical models in order to solve symbolic optimization problems. In GP, computer programs with a tree-shape structure are first generated. Then, these programs are encoded with genes, that can evolve using an evolutionary algorithm, and are expressed through expression trees (see Fig. 1). An expression tree is hierarchically structured and contains functions and terminals. For instance, a function, *F*, may comprise of mathematical operations (+, – etc.), logic functions (AND, OR, etc.), etc. and the terminal, *T*, contains the arguments for the functions (e.g. numerical/logical constants, variables, etc.). An expression tree can inversely be converted into a Karva notation (K-expression) by recording the nodes from left to right in each layer while simultaneously maintaining the order from top-most layer down to the deepest layer.

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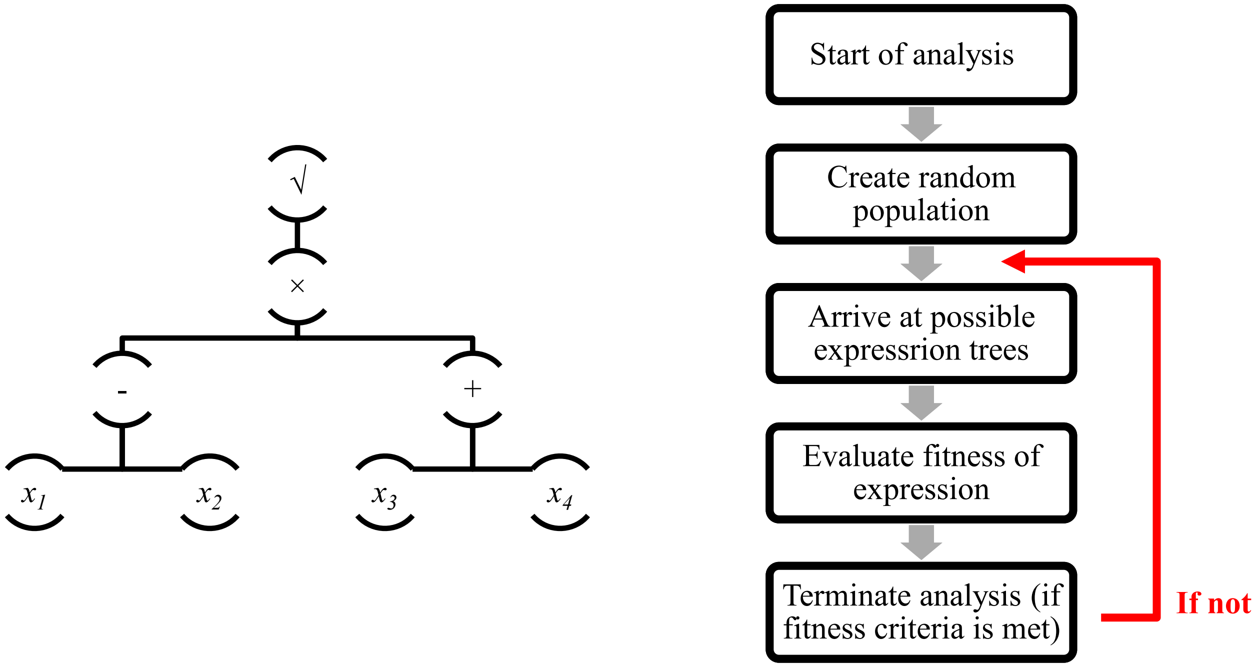

(a) Representation of a typical expression tree:

$$\sqrt{(x_1 - x_2)(x_3 - x_4)}$$

(b) Flowchart of analysis procedure

Fig. 1 Details of GP analysis

The main steps that GP follows to arrive at a suitable solution are complex as they utilize a series of operations (i.e. crossover, mutation and rotation etc.) and for brevity are avoided here but can be found elsewhere (Ferreira, 2001). It is worth noting that a GP analysis is terminated once a functional form of a tree (i.e. mathematical expression or equation) satisfies a fitness function; where a fitness landscape is equivalent to an objective function that describes the optimality of an expression's predictions against predictions from all the other generated expressions (see Fig. 1b).

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2.2 Computer vision (CV)

Computer vision (CV) is another subfield of ML that trains computing stations (computers) to interpret and understand visuals obtained from imagery and videos. Problems of primary interest to CV involve those where objects are to be correctly identified (detected), classified and labeled with minimum to no human intervention as to produce quantitative or symbolic outcome (see Fig. 2). Early works on CV started in 1950-70s to identify simple objects and then evolved to interpret written text for the visually impaired. Then, extensive amount of research was directed towards CV in 1990s as a result of internet and ease of access to large set of imagery (Szeliski, 2010). It is worth noting that such research mainly targeted applications associated with facial recognition, security and medicine.

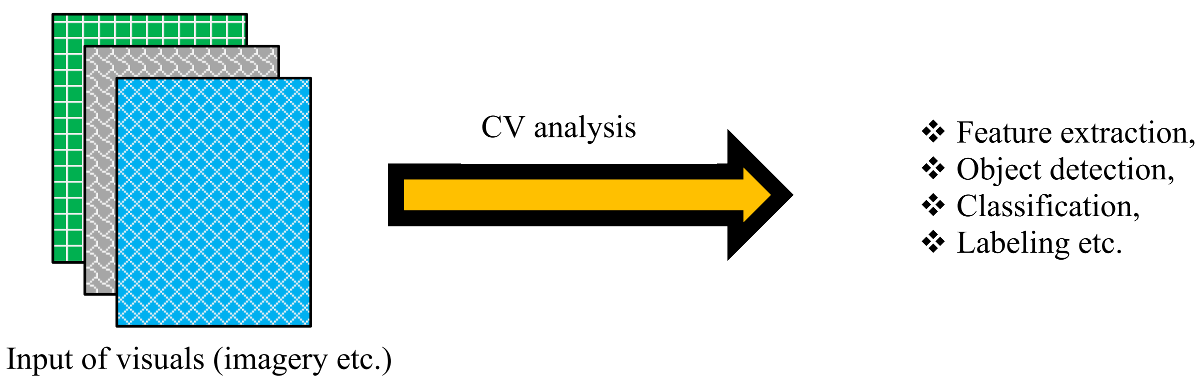

Fig. 2 Representation of CV analysis process

Computer vision is primarily applied through algorithms and techniques utilizing specific forms of ANNs that can mimic the cognition process of the brain. ANNs are generally designed to have a number of layers in which the first layer receives input data points and the last layer presents the outcome of the CV analysis. CV-based ANNs have a series of hidden layers, where each successive layer utilizes the output from the previous layer as input, in order to learn and understand multiple levels of representations – this is often referred to as deep learning. Some of the commonly used ANNs include; Region-based Convolutional Neural Network (R-CNN), Single-Shot Detector (SSD) etc. While these derivatives share some features in common, they still differ on a number of fronts; primarily due to the nature of their development and intended use (Sutskever et al., 2014).

3.0 Insights into Rationale Behind Development of Databases and A&C Models

This section highlights the main rationale behind developing the two ML-based models used in this study; a GP model and a CV model. The main aspects of these models are discussed in detail herein.

3.1 GP model

The developed GP model is designed to understand behavior of RC beams and columns during as well as in the aftermath of being exposed to fire. As such this model is trained to identify key parameters that govern fire response of RC beams and columns as to enable quick evaluation of fire resistance as well as residual (post-fire) capacity of these structural members. This evaluation can be carried out through simple, one-step, expressions that comprehend the naturally complex behavior of fire-exposed RC structural members and implicitly take into account high temperature material properties of concrete and steel reinforcement, as well as associated phenomena; i.e. creep and spalling to certain extent, and thus does not require input of temperature-dependent material properties or thermo-structural analysis nor distinct simulation/analysis software. This GP model was developed in Matlab environment and similar models could also be developed using freely available codes e.g. GPTIPS (Searson, 2009) or commercially available software such as Discipulus (2015).

The developed GP model recognizes that when a RC member is exposed to fire conditions, cross-sectional temperature in this member slowly rises due to the low thermal conductivity and high heat capacity of concrete. Thus, a thermal gradient develops in which the temperature at the exposed surface of concrete is much higher than that at the level of embedded steel reinforcement or inner concrete layers. As the temperature further rises within the cross-section, additional layers of concrete, together with steel rebars, heat up leading to degradation in strength and modulus properties. With the continuous rise in temperature, combined with stresses developed from applied loading (e.g. point load as shown in Fig. 3a), losses in mechanical properties causes the structural member (i.e. beam) to soften. At this point, the beam is weakened due to the combined effects of thermal and gravity loads, experiences rapid rise in deflection, and fails once the magnitude of applied loading exceeds the level of moment capacity.

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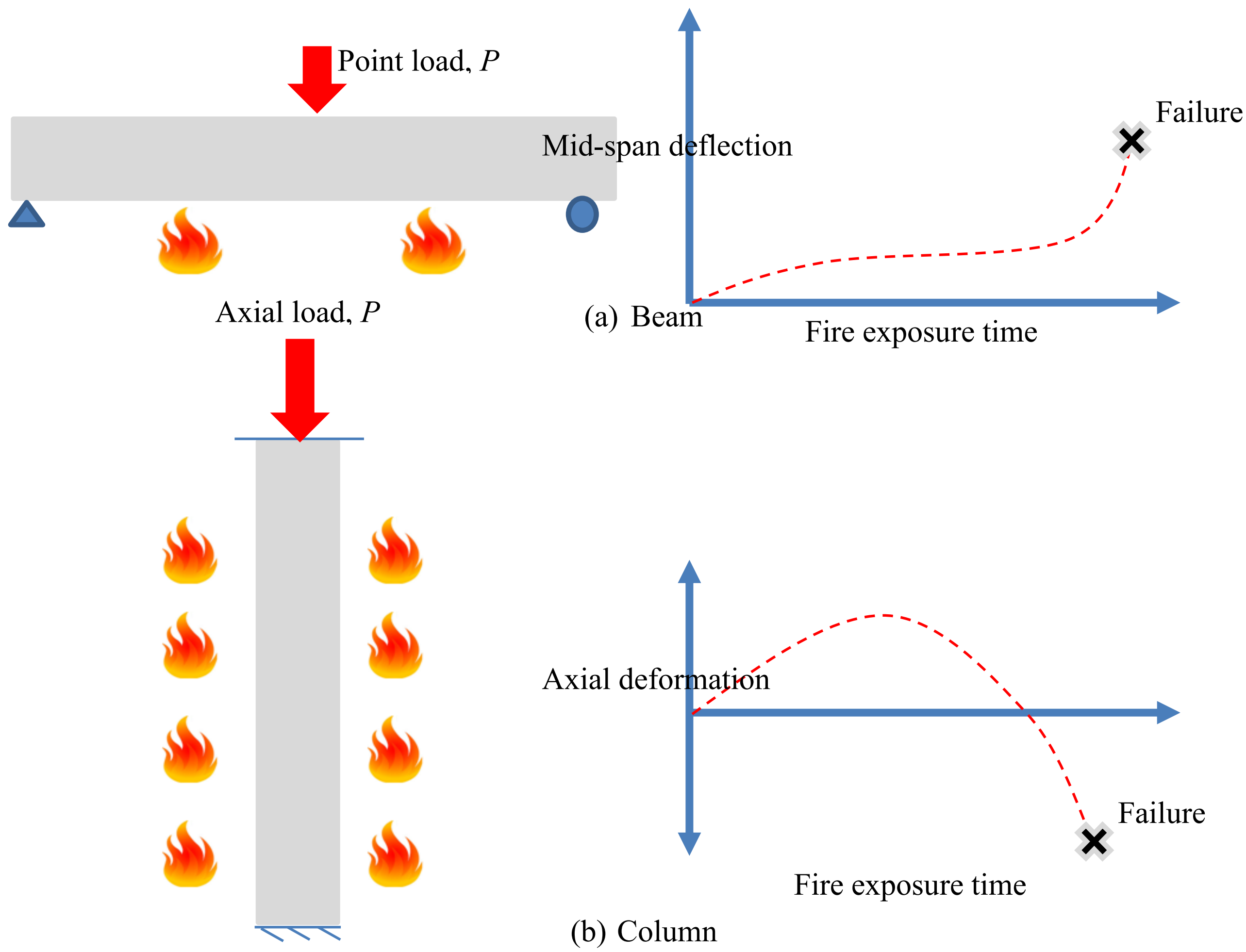

Fig. 3 Typical response of RC beams and columns under fire conditions

In the case of columns, a fire-exposed RC column vertically expands in response to rise in temperature (see Fig. 3b). During later stages of fire exposure, and due to the rise in cross-sectional temperature and associated degradation in strength properties, the column starts to weaken. This corresponds to a contraction stage in which the axial deformation of the column shifts from expansion into contraction. Eventually, with the increase of fire exposure duration, which continues to cause further losses in mechanical properties of constituent materials, the column fails. In all cases, and especially in a timed fire resistance test, a RC beam or column may not fail before the test is completed (i.e. in case the required fire rating is achieved or in the event that the beam or column was only heated and not subjected to mechanical loading). In this scenario, it is possible to mechanically test the member (once it cools to ambient conditions) to evaluate its residual capacity.

The GP model recognizes the above phenomena and with the aid of engineering judgement as well as observations of previous fire tests (Albuquerque et al., 2018; Ali et al., 2004; Bai and Wang, 2011; Carlos et al., 2018; Davey and Ashton, 1953; Dotreppe et al., 1997; Ellingwood and Lin, 2007; Hsu and Lin, 2008; Jiangtao et al., 2017; Kodur et al., 2000, 2001, 2005, 2003; Kodur and Phan, 2007; Kodur and McGrath, 2003; Lie and Woollerton, 1988; Lin et al., 1992; Myllymaki and Lie, 1991; Rodrigues et al., 2010; Shah and Sharma, 2017; Thomas and Webster, 1953; Yu and Kodur, 2014; Zhu et al., 2014), this study hypothesizes that in order to obtain the time at which a RC beam or column fails under exposure to standard fire, all that is needed is few parameters comprising geometric features, material properties, as well as configuration of loading applied during fire etc. (see Table 1 for a complete list of parameters). Thus, the objective of the developed GP model is to establish a relation that best represent above parameters to yield accurate predictions of fire resistance and post-fire capacity of RC beams and columns. Although such relation is complex as it is a function of multi-dimensions/parameters, still this function can be obtained by applying A&C/ML. Simply put, the rationale behind GP modeling is that since the a phenomenon (i.e. time to failure etc.) is of interest, and since this phenomenon is observed/measured in fire tests, then a relation connecting such effect to loading conditions as well as material characteristics and geometric features can be arrived at.

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Table 1 Selected parameters for use in GP modelling

Parameter/Case		**Input parameters**									**Output parameters**	
		Compressive strength of concrete (f_c)	**Yield strength of steel (f_y)**	**Steel reinforcement ratio (r)**	**Span length (L)**	**Load magnitude/level (P)***	**Cover to steel reinforcement (c)**	**Loading eccentricity (e)**	**Exposure time under standard fire (T)**	**Tie spacing (S)**	**Failure time (t)**	**Residual capacity (R_{cap})**
During fire	**Beams**	✓	✓	✓	✓	✓	✓	-	-	-	✓	-
	Columns	✓	-	✓	-	✓	✓	-	-	-	✓	-
Post-fire	**Beams**	✓	✓	✓	✓	✓	✓	-	✓	-	-	✓
	Columns	✓	✓	✓	-	-	✓	✓	✓	✓	-	✓

*Portion of moment capacity (%) in beams and applied loading (kN) in columns

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As shown in Table 1, two databases were compiled for RC beams and columns; one for those tested under fire conditions and the other for tests carried out to evaluate residual capacity (post-exposure to fire[‡]). In each test, critical parameters (i.e. fire resistance and residual capacity) are collected together with relevant input parameters listed in Table 1 (i.e. compressive strength of concrete (f_c), yield strength of steel (f_y) etc.). Tabulating these datapoints allows the GP model to relate output of a given test to geometric, material and loading features as to derive an expression that relates associated inputs and outputs. This procedure implicitly accounts for temperature-dependent material properties and eliminates the need to develop sophisticated FE models and to carry out thermal and/or structural analysis. All in, the developed GP model is accommodating and can account for other input variables (i.e. moisture content of concrete etc.) once/if such data is reported and accessible. Concerns with regard to datapoints homogeneity and unbiasness as well as numerical processing/handling techniques that can be applied to facilitate such issues are addressed in companion works (Naser 2019a; b).

3.2 CV model

To show the merit of adopting A&C technologies, two CV models were developed through the commercially available ML-based image recognition platforms; Clarifai (2019) and Deepomatic (2019)[§]. Since these two platforms have been recently verified and successfully applied in a wide spectrum of industries (i.e. healthcare, construction etc.), these are also deemed suitable to examine fire response of structures. The first step in carrying out a CV analysis is to

[‡]These databases can be downloaded at www.mznaser.com/fireassessmenttoolsanddatabases.
[§]Similar models can also be developed using specifically-designed R-CNNs (Redmon and Farhadi, 2016).

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understand the phenomenon on hand as to select a suitable strategy for analysis. From this point of view, the identification of fire-induced spalling damage falls under classification and detection categories. In classification, a CV model aims to label (i.e. classify) a particular object based on its features through extracting visual cues and information and then determining which category best fit this item/object. For example, the CV model is expected to label an image of a "fire-induced spalling of concrete cover" as "fire-induced spalling of concrete cover" and not as a "cracking" or "crushing" of concrete etc. On the other hand, detection implies the successful capability of a CV model to detect pre-identified features in a given visual (e.g. to correctly pinpoints regions of major, minor and mild spalling as well as regions that did not spall). Now that the analysis categories are identified, the next step is to collect imagery pertaining to such phenomenon. This study compiled 300 images taken from open literature and from fire tests carried out on RC beams and columns. In order to provide a variety of examples, these images varied in color scheme (black and white/colored), view angle (side/top/isometric), and size (large vs. small specimens) etc.

Computer vision is a semi-supervised ML technique that is primarily applied through utilizing specific forms of ANNs that can mimic the cognition process of the brain. In this case, the CV model is expected to properly classify and detect the magnitude of spalling in fire-exposed concrete members and to correctly detect the regions of a RC specimen in which any magnitude of spalling (e.g. mild/minor/major spalling) occur. It should be noted that the magnitude of spalling is deemed: 1) "major" if large chunks of concrete fell-off or if concrete cover spalled exposing internal steel reinforcement directly to heat, 2) "minor" if a portion of concrete cover fell-of thus not exposing internal reinforcement to fire, and 3) "mild/no" if cosmetic damage and/or no spalling occurred to the surface of the member. A sample of varying levels of fire-induced spalling is shown in Fig. 4 and the complete set of imagery used in this study can be found and downloaded at www.mznaser.com/fireassessmenttoolsanddatabases.

Fig. 4 Demonstration of magnitude of spalling used in training the developed CV model – Specimen B5 taken from Dwaikat and Kodur (2010) with permission.

4.0 Fire Resistance Evaluation through A&C

The above discussion demonstrates how A&C requires the development of databases collected from previously published works/reports/studies/fire tests. As such, a brief description of some of the selected fire tests is presented herein. For brevity, full details on those tests, together with other tests as well as information covering specifics on test set-ups, loading arrangements and conditions, material properties etc. can be found in respective references.

In one study, Palmieri et al. (2012) carried out twelve fire tests on FRP-strengthened RC beams; out of which two beams were uninsulated and unstrengthened. These beams had a height and width of 300×200 mm, a clear span of 3150 mm, were reinforced with tensile reinforcement consisting of 2 bars of 16 mm diameter and failed at 65 and 105 minutes after being exposed to ISO 834 fire conditions. Choi and Shin (2011) also tested two RC beams made of normal strength concrete with cover to tensile reinforcement of 40 and 50 mm, respectively. The beams were of rectangular shape: 250 mm (width) × 400 mm (depth), spanned 4700 mm, were exposed to ISO834 fire and failed in 160 and 220 min. On a parallel note, only few studies that examine residual response of fire-exposed RC beams are available. For instance, Kumar and Kumar (2003) carried out five tests on RC beams in order to examine their residual capacity post exposure to the ISO 834 fire. These tests showed that RC beams exposed to 1 and 2 hours of standard fire can retain 83% and 50% of their room temperature capacity, respectively. Another study was carried out by Kodur et al. (2010) in which one beam was made of normal strength concrete (NSC) while another beam was made of high strength concrete (HSC). These researchers reported that these beams retained significant flexural capacity after exposure to fire. In lieu of above works, the following studies were also used to developed databases on fire-tested RC beams (Albuquerque et al., 2018; Bai and Wang, 2011; Carlos et al., 2018; Ellingwood and Lin, 2007; Hsu and Lin, 2008; Jiangtao et al., 2017; Wu et al., 1993; Yu and Kodur, 2014; Zhu et al., 2014).

In the case of columns, Hass (1986) tested 39 square and rectangular columns made of normal strength concrete under ISO 834 fire conditions. In these tests, two sections were studied: 200×200 mm^2 and 300×300 mm^2 reinforced with 14 or 20 mm rebars. The major factors investigated in this program included load level, concrete strength, and ratio of reinforcing steel rebars. During 1980s-1990s, the National Research Council of Canada (NRCC) established a series of programs designed to examine fire resistance of RC columns made of normal and high strength concrete as well as high performance concrete. These tests investigated fire response of more than 60 columns of varying shapes and cross-sectional dimensions, percentage of steel reinforcement, compressive strength of concrete etc. Some of the other fire tests on RC columns that were reviewed and included in the developed databases can be found elsewhere (Ali et al., 2004; Davey and Ashton, 1953; Dotreppe et al., 1997; Kodur et al., 2000, 2001, 2005; Kodur and

McGrath, 2003; Lie and Woollerton, 1988; Lin et al., 1992; Myllymaki and Lie, 1991; Rodrigues et al., 2010; Shah and Sharma, 2017; Thomas and Webster, 1953) etc. Of the few testing programs carried out to examine residual response of fire-exposed RC columns are those by Lie et al. (1986), Lin et al. (1989), and Kodur et al. (2017, 2013). The outcomes of these tests are also collected and utilized in this work.

4.1 GP analysis

As discussed above, the GP analysis was carried out in Matlab software as per procedure outlined in Sec. 2.1 and 3.1. Out of all databases, 70% of this data is used to train the GP model and 30% is evenly split to validate and then test the performance of the developed expressions – a notion that has been well established by previous works (Chandwani et al. 2015; García-Segura et al. 2017; Naser 2019a; b). The outcome of this analysis, in terms of derived expressions that can be used to evaluate fire resistance as well as residual capacity of RC beams and columns are listed in Table 2, together with their fitness metrics (i.e. coefficient of determination (R^2), correlation coefficient (R), and mean average error (MAE)) as well as number of specimens used in GP analysis and range of applicability for each expression. The associated fitness metrics of these expressions, in addition to validation plots shown in Fig. 5, demonstrate the validity and accuracy of these expressions. It is worth noting that a second stage of validation was also performed using supplementary observations from additional fire tests that were not included in the initially developed databases. These additional tests were used to verify the validity of these expressions – an example on such additional validation is presented in the appendix.

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The reader is encouraged to remember that these expressions represent the GP-obtained relation between inputs and output to signify a given phenomenon and hence these expressions do not share similar resemblance to those commonly used and/or arrived at through classical/theoretical/analytical derivation. While the later expressions can be used to estimate fire resistance or residual capacity of a fire-exposed member through an iterative/lengthy procedure that requires obtaining cross-sectional temperature at various points in time and collection of temperature-dependent material properties, the GP-derived expressions on the other hand can evaluate the same phenomena through a one-step substitution process that only requires input of room temperature material properties and geometric configurations as shown in the example provided in the appendix.

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348 Table 2 Expressions to evaluate fire resistance and residual capacity of RC beams and columns

Case		No. of specimens	Derived expression	R^2	R	MAE	Range of applicability
Fire resistance	Beams	26	$t = 47.57 + 1.37C + rL + \frac{f_y}{f_c} + \frac{20.65\left(\frac{293.03f_y}{f_c}\right)}{f_y} - 66.47cos(3.46 \times 10^3 P)$	95.3	97.6	9.7 min	C = [25-40 mm] f_c = [15 – 92 MPa] f_y = [240 – 591 MPa] L = [1.75 – 6.5 m] P = [0 – 85%] r = [0.37 – 1.14%] t = [60 – 240 min]
	Columns	139	$t = 79 + C + \tan(73.97 - f_c) + \cosh(4.72\tan(C)) + \tan\left(98.64 - \frac{1.04P}{r}\right) - Ctan(f_c) - \tan\left(3.57 \times 10^4 - \frac{1.1P}{r} - 103.3f_c\right)$	85.3	92.5	19.5 min	C = [15 – 48 mm] f_c = [15 – 60 MPa] P = [0 – 3500 kN] r = [1 – 4%] t = [60 – 240 min]
Residual capacity	Beams	9	$M_{res} = 38.17 + 0.0191(C + rL) + \frac{1.2}{\cos(4.01+T)} - 41.7sin(f_y) - 41.7sin(f_c)$	96.0	98.3	8.9 kN.m	C = [25 – 30 mm] f_c = [17 – 52 MPa] f_y = [358 – 480 MPa] L = [1.80 – 4.90 m] r = [0.65 – 1.47%] T = [30 – 120 min]
		29	$V_{res} = 1943 + 51.63\sin(f_c) + 0.569ST + 5.39qrT - \frac{953d}{b} - r\sqrt{1943 + rS} - 90.34T - 114.5q$	86.2	92.8	33.6 kN	b = [200 – 300 mm] d = [240 – 380 mm] f_c = [35 – 70 MPa] q = [1.5 – 4] r = [1.5 – 4.8%] S = [0 – 150 mm] T = [1 – 3 hrs]

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	Columns	55	$P_{res} = f_y + \frac{15.5f_c}{r} + T - 103e - 2.38 \times 10^3 cos(2.54 + C) - 0.0738\left(\frac{f_c}{r}\right)^2 - 2Ssin(11.9S)$	91.1	95.5	258 kN	C = [38 – 64 mm] f_c = [13 – 21 MPa] f_y = [351 – 368 MPa] e = [0 – 20 mm] P = [0 – 85%] T = [30 – 240 min] S = [150 – 305 mm]

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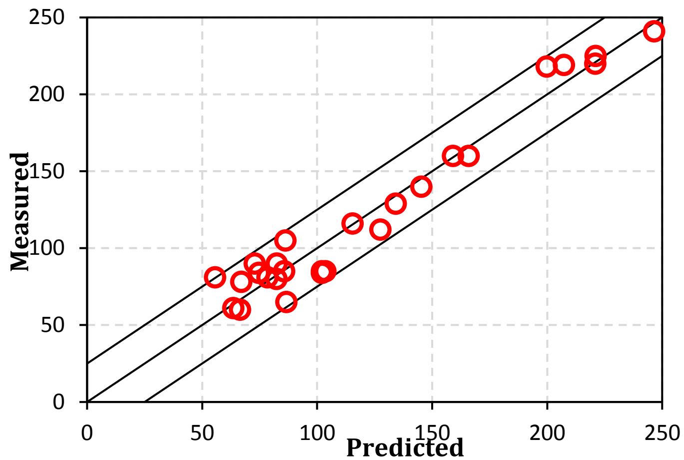
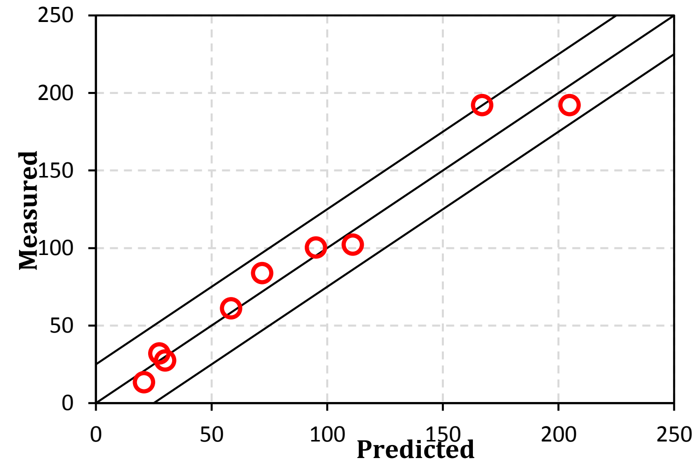
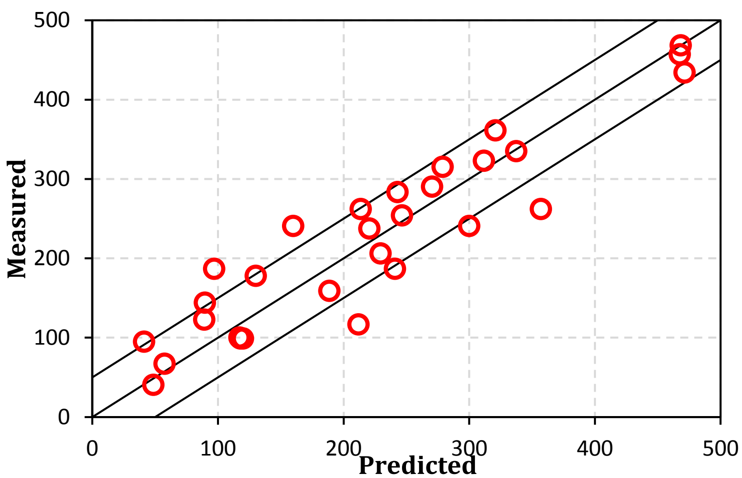
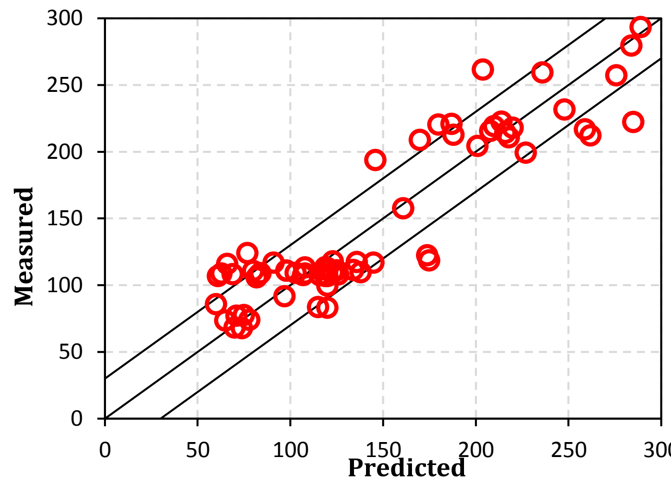


(a) Fire resistance of beams (in min)



(b) Residual moment capacity of beams (in kN.m)





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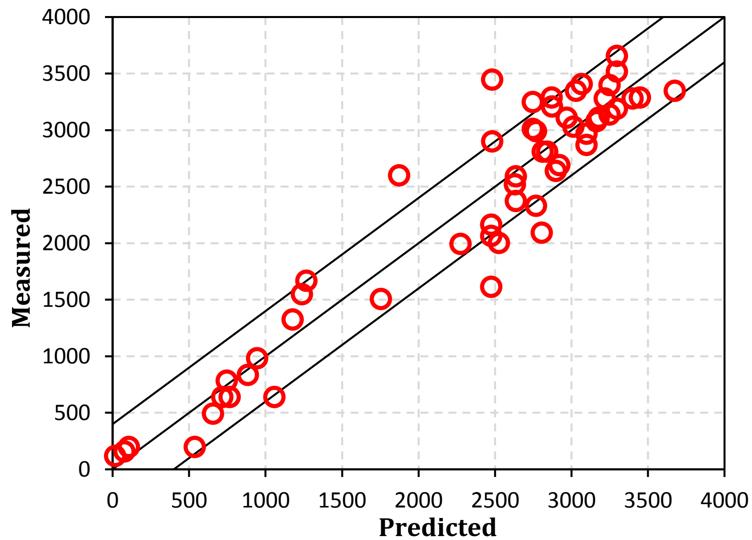
(c) Residual shear capacity of beams (in kN.m)

(d) Fire resistance of columns (in min)



(e) Residual capacity of columns (in kN)

350 Fig. 5 Validation and performance of predictions obtained from GP analysis (uncertainty slopes located at 10%)

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A look into the number of used specimens in the carried out analysis shows the general availability of a much larger sample size in the case of columns than beams. The same look also points out that it is unfortunate that only few research programs examined residual response of RC beams. It is worth noting that some of the currently published studies in this area applied fires of much higher intensity than the standard fire and/or applied a controlled cooling phase or did not provide full details on tested specimens (Agrawal and Kodur, 2019; Jayasree et al., 2011; Kumar et al., 2009; Lin et al., 1999). In order to maintain homogeneity of developed databases, observations from such fire tests were not included herein as they require special processing and transformation. These observations are currently being analyzed as part of a future work. Overall, the presented outcome represented in fitness metrics listed in Table 2 and Fig. 5 show the merit of: 1) A&C in understanding structural fire engineering phenomena, 2) developing simple expressions for fire evaluation using GP, and 3) scalability of GP analysis in accommodating varying levels of sample sizes and input parameters. In future works, and with the availability of additional observations from fire tests, the GP model is expected to improve its predictability and accuracy (refer to Sec. 5.0 for additional details).

4.2 CV analysis

The performance of the developed CV models can be evaluated through quantitative metrics implemented in Deepomatic and Clarifai as well as by examining the accuracy of predictions taken against new raw data (i.e. images) that were not used in the training or validation procedure of the CV models. For example, in Clarifai, the model accuracy score is the main metric that describes the performance of the developed CV-model. This metric is defined as macro

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average of the **a**reas **u**nder the receiver operating characteristic **c**urve (AUC) for every defined concept[**]; and hence a score of unity represents a perfect score. The average accuracy of the developed model herein is 88.8% (with individual accuracy for the identified three concepts: major, minor and mild spalling equals to 93.4%, 78.8%, and 94.1%, respectively). The prediction capability of the CV model is also tested by inputting a series of images that were not included in the training and validation process i.e. exposed to the model for the first time. The prediction capability of the developed model in classifying spalling magnitude in a RC specimen that examines for the first time is shown in Fig. 6. A look into Fig. 6 shows that the developed model was able of accurately identifying fire-induced spalling state as "major spalling" with a probability of 99% as opposed to "minor spalling" with a probability of 11%. This prediction is accurate as the depicted specimen has lost concrete cover along its edge thus directly exposing internal steel reinforcement to fire conditions. This agrees with the applied definition of major spalling as described in Sec. 3.2.

[**]Where concepts refer to "major", "minor" and "mild" spalling.

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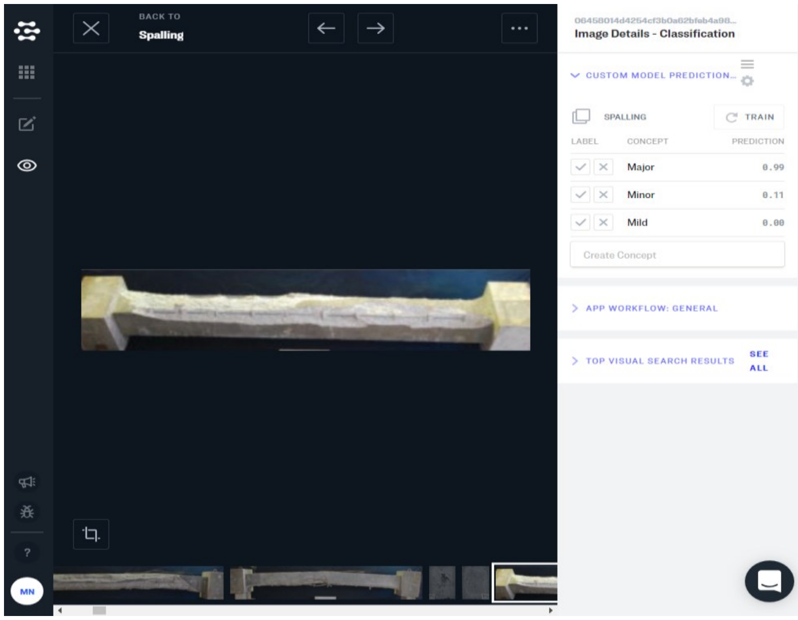

Fig. 6 Image classification through Clarifai – fire-tested RC specimen "C2-1-25" taken from Tan and Nguyen (2013) with permission.

Another mean to evaluate the accuracy of the developed CV model is to examine "concept by concept matrix". In general, this matrix can be read by fixing each row where each row represents a subset of the analyzed data that was actually labeled with a specific concept. A similar matrix, referred to as "co-occurrence matrix", shows concepts that co-occur through a visual cluster. It can be seen from Table 3 that this model was properly trained and validated.

Table 3 Metrics for developed CV models

Concept by concept matrix (%)		**Predicted**		
		Major	Mild	Minor
Actual	Major	0.855	0.102	0.348
	Mild	0.020	0.759	0.257
	Minor	0.103	0.143	0.290
Co-occurrence matrix (counts)		**Predicted**		
		Major	Mild	Minor
Actual	Major	172	1	3
	Mild	1	59	2
	Minor	3	2	58

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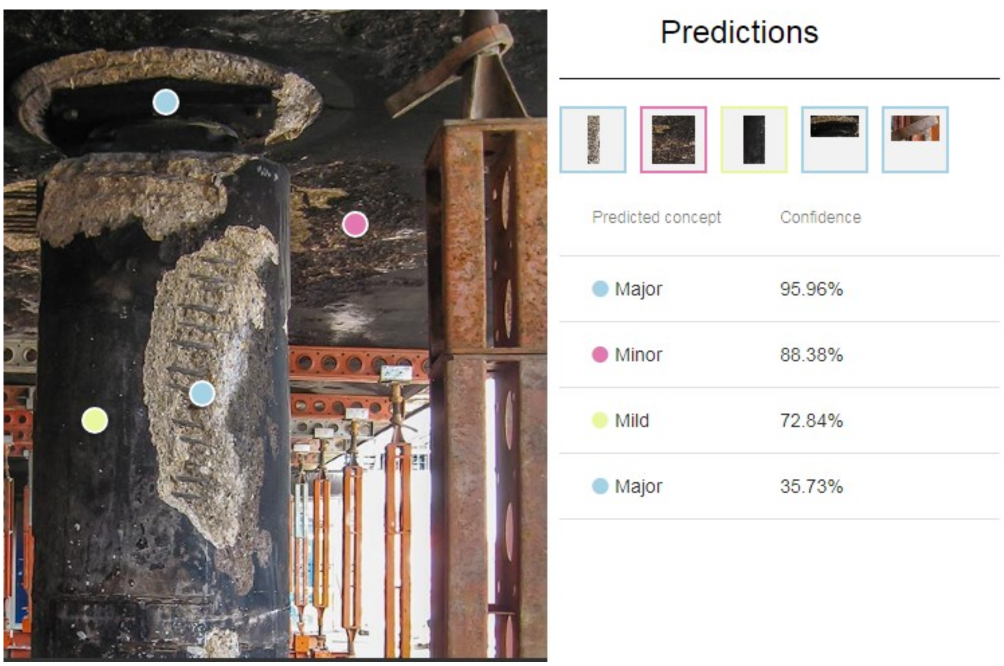
Unfortunately, Clarifai can only classify images as whole and cannot pinpoint regions where spalling of varying magnitudes occurs. On the positive side, Deepomatic is able to identify such regions, and similar to Clarifai, also lists the confidence of its predictions in identifying these regions. Figure 7 shows few examples demonstrating the capability of Deepomatic in identifying spalling levels post-fire incident (Fig. 7a) as well as post-fire test (Fig. 7b). It should be noted that both of these examples were part of the additional validation process and were not included in the imagery used to train the CV model. As can be seen from this figure, it is clear that the developed model can properly identify the magnitude of spalling in both cases and also pinpoint the location of such spalling.



(a) Detecting of spalling magnitude post fire incident

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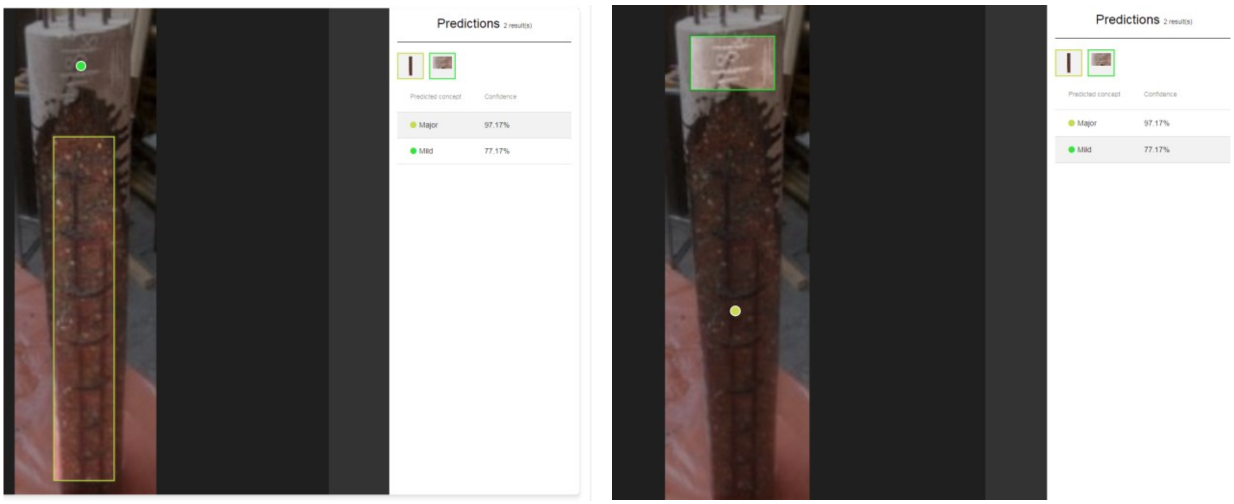

(b) Detecting of major spalling (c) Detecting of mild spalling

Fig. 7 Detection of magnitude of spalling through CV analysis (bottom images taken from Yaqub and Bailey (2011) – with permission)

Overall, it is worth noting that the development, evaluation and deployment of the above two models can be completed within 1-2 hours (with Deepomatic being slightly more resource intensive as it requires additional processing to be able to identify and label the specific regions that spalled – unlike Clarifai which classifies images as a whole). It is expected that this tool can be deployed to smart cell phones and/or unmanned vehicles (i.e. drones) such that proper assessment of post-fire incidents can be carried out on-site and immediately. An ongoing project is currently verifying the implementations of this technology on a larger scale.

5.0 Automation and Cognition in Structural Fire Engineering

It can be inferred from the above discussion that adopting A&C as an assessment tool negates much of the limitations associated with traditional fire evaluation methods whether experimental or numerical – especially those related to scalability, feasibility and multi-stage analysis and standardization/validation. However, the reader must also realize that the seamless simplicity of A&C (or ML in general) can be deceiving and a thorough understanding of how to

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properly apply this technology is warranted – given that most civil/fire engineers are classically trained and may not be skilled in fields such as data analytics (Rabuñal, 2005). This section highlights some of the limitations, challenges and future research needs associated with utilizing A&C into practical fire-based field applications.

5.1 Limitations and Challenges

Unlike traditional fire assessment methods, autonomous fire resistance evaluation does not only rely on the outcome of a single fire test but rather on a collection of fire experiments to realize a phenomenon. Thus, it is of utmost importance to note that A&C approaches are expected to be used in conjunction with traditional methods and may not substitute well-established methodologies – not until a thorough and systematic verification is carried out. Due to the nature and need for lesser number of input parameters, simple computations as well as rapid advancements in ML, this verification is expected to be realized much sooner than that in traditional/numerical evaluation methods.

Due to the naturally niche area of fire engineering, much of the published tests and data used in this study were obtained from results of standard fire testing. In such tests, RC beams and columns often share similar features (i.e. size, restraint conditions etc.) that may not be reflective of in-situ conditions. Tested elements were also exposed to one temperature-time curve i.e. standard fire condition. As such, the application of the GP-derived expressions is to be applied to RC beams and columns of similar features to those used in the development of such expressions and described in Sec. 4.1.

In a similar manner, the imagery used to develop the CV model were mainly collected from the outcome of published fire tests – with some images taken from findings of post-fire site investigations. Since the bulk of these images show a clear view of single elements (or portion of elements), the CV model may not properly capture spalling occurrence (or intensity) throughout the whole fire-damaged elements or in areas covered in soot. Another limitation worth noting is the inability of the current CV model to quantitatively predict the magnitude of spalling (i.e. analyzing the image to estimate the overall spalling magnitude (say, 17% of concrete cover spalled) and how much such spalling can affect the residual capacity of the fire-damaged member.

5.2 Future Research Directions

Despite the above challenges, the findings of this work still provide a good starting point for training A&C architectures. Future works are encouraged to find solutions to overcome some of the above identified limitations through collaboration with interdisciplinary scientists. For example, a key future research direction must address the development of ML models that are specifically optimized for structural fire engineering problems. Such models are to be capable of comprehending fire-related phenomena as to yield realistic and reliable predictions.

Arriving at an acceptable/uniform representation of the fire phenomenon is the first step towards standardization and acceptance between researchers, industry practitioners and government officials. This unified representation is to be arrived at through analysis of a large number of useful and reliable data points with limited margin of variability. The availability of such data points that are comprehensive and repeatable is without a doubt limited within our structural fire engineering community given the scarcity of available fire tests, especially those carried out with duplicated specimens (Shahin et al., 2009). Thus, future testing programs are encouraged to allocate room for duplicated tests[††], properly document the outcome of their findings/observations, and share such findings in a timely matter; and when possible on dedicated/easily/freely accessible servers. As such, development of A&C models can be expedited as to yield higher accuracy and wider applicability than those developed using case-specific analytical and FE models.

Future works are also urged to develop algorithms that can relate magnitude of damage (i.e. major and minor spalling) to reduction in member volume, sectional capacity and be able to propose solutions to retrofit fire-damaged structures. These works are also expected to focus on complex phenomena such as buckling in steel members, charring in timber members, as well as fire response of other structural systems such as frames, connections, etc. Finally, a fire researcher/engineer is to remember to establish a line between accuracy and computational feasibility and to steer away from chasing "perfect fitting", as unlike other loading conditions, the phenomenon of fire is highly random and complex occurrence.

6.0 Conclusions

This paper showcases how automation and cognition, as part of machine learning, have the potential to revolutionize assessment of structural members exposed to fire conditions and could be the solution to facilitate performance-based fire design of structures. The following conclusions could also be drawn from the results of this investigation:

[††]Out of all reviewed fire tests, only those conducted by the National Building Studies (Davey and Ashton, 1953; Thomas and Webster, 1953) specifically tested additional RC columns to ensure test repeatability.

- Modern technologies such as A&C, together with ML derivatives, form the foundations for future and autonomous fire evaluation methods.
- Currently available A&C platforms (such as GP and CV) are capable of detecting damage arising from fire loading with ease and high accuracy (within 85-96% range). Such platforms can be obtained through freely/commercially available software or can also be specifically coded for phenomena-oriented deployment.
- Despite the merit of integrating A&C frameworks into structural fire engineering applications, there are few challenges that continue to hinder full deployment of such frameworks (i.e. limited availability of comprehensive datapoints etc.). Fortunately, future A&C models would be able to overcome such challenges.

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Compliance with ethical standards

The author declares no conflict of interest.

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8.0 Nomenclature

A_{res}	Residual axial capacity
b	Beam width
c	Cover to steel reinforcement
d	Beam depth
e	Loading eccentricity

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f_c	Compressive strength of concrete
f_y	Yield strength of steel
L	Span length
M_{res}	Residual moment capacity
P	Load magnitude/level
q	Shear span–depth ratio
R	Steel reinforcement ratio
R_{cap}	Residual capacity
S	Tie spacing
T	Exposure time under standard fire
t	Failure time
V_{res}	Residual shear capacity

9.0 Appendix

An example illustrating application of PG-derived expressions to evaluate post-fire shear capacity of a typical RC beam is listed herein. This beam is taken from the fire tests carried out by Lin et al. (1999). This beam had a width (*b*) and depth (*d*) of 300 mm by 360 mm. The compressive strength of concrete (f_c), steel reinforcement ratio (*r*), and stirrup spacing (*S*) in this beam were 36 MPa, 1.72%, and 150 mm respectively. This beam was subjected to the ASTM E119 fire scenario (*T*) for 3 hours and then was left to cool down naturally. The measured shear capacity of this beam was 312 kN obtained at shear span–depth ratio (*q*) of 4.0. Using the above GP-derived expression, the post-fire residual shear capacity of this beam can be evaluated as:

$$V_{res} = 1943 + 51.6\sin(f_c) + 0.569ST + 5.39qrT - \frac{953d}{b} - r\sqrt{1943 + rS} - 90.34T - 114.5q$$

$$V_{res} = 1943 + 51.6\sin(36) + 0.569 \times 150 \times 3 + 5.39 \times 4 \times 1.72 \times 3 - \frac{953(360)}{300} - 1.72\sqrt{1943 + 1.72 \times 150} - 90.34 \times 3 - 114.5 \times 4 = 322.8\ kN\ (within\ 4\%\ differnce\ than\ measured\ value).$$