Digital Analysis of Historic Bridge Images

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Abstract: This short paper summarizes work-in-progress to create a database of 4800 electronic images of historic American and Canadian highway, railway and pedestrian bridges constructed between 1865 and 2019. The images were retrieved from Wikipedia, Wikimedia Commons, and the Historic American Engineering Record (HAER) websites. Machine-vision systems and image-processing techniques are applied to determine whether a bridge is present in the image, the form or type of bridge, the date of construction and other features. The Artificial Intelligence classification identifier was 85–92% accurate when distinguishing between girder and through-truss bridge types and roughly 70% accurate when distinguishing between cantilever, through-arch, girder, through-truss and deck arch bridges types. It is perhaps more challenging to determine the date of construction because time is a continuum. The temporal evolution of bridge types and construction details is somewhat blurry and varies between different geographic regions. Some configurations, such as covered bridges and Pratt Truss bridges, haven't evolved significantly for quite some time. A possible next step will be to use image-processing and photogrammetric techniques to try to identify the vantage point from which the bridge was photographed. The relevance of this study extends beyond those interested in historic bridges to scholars studying image classification in other areas of the digital humanities.

Keywords: *Artificial Intelligence—Automatic Identification Systems—Highway Bridges—Historic Images—Machine Learning*

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Introduction

This short paper summarizes work-in-progress to create a database of electronic images of historic bridges. These images are being used concurrently to develop machine-vision systems and image-processing techniques to automatically identify, in historical and contemporary images of cityscapes and landscapes: (1) the presence of a bridge or bridge component in an image; (2) the form (or type) of bridge or bridge component; (3) the age and other features; and (4) the vantage point from which the bridge was photographed.

Database of Historic Bridge Images

A database of 4800 images of Canadian and American highway, railway and pedestrian bridges constructed between 1865 and 2019 has been created and continues to be extended. The images were retrieved from Wikipedia, Wikimedia Commons, and the Historic American Engineering Record

(HAER) websites. Many American bridges are listed on the U.S. Department of the Interior's National Register of Historic Places, although those less than 50 years old are ineligible for this recognition.

Each bridge is assigned a unique identifier and is associated with the fields shown in Table 1. The Wikidata identifier links records in the bridge table with open data. A sample record (for the Lions' Gate Bridge in Vancouver, BC) is available at https://www.wikidata.org/wiki/Q124352. Among other things, it contains the designer, the date the bridge was officially opened, the longest span, heritage designation, identifiers for other databases and translations of the bridge's name into other languages.

Table 1: Fields to Define Bridges

Field	Contents
Name of Bridge	Text
Bridge ID (primary key)	Number
Wikidata ID	Concept URI (to link record to open data)
Location	City/Town/County, State (Province), Country
Date of Construction	Year
GPS Location	Latitude, Longitude
Main Span Type	Main Span Type ID (foreign key to Table 2)
Approach Span Type	Deck arch, Deck truss, Girder, Half-through arch, Half-through truss, Through arch, Through truss or NULL

Each bridge is characterized by a Main Span Type, shown in Table 2. Most of the Main Span Type Classifications include Subclassification options. Each combination of Classification and Subclassification is assigned a unique Main Span Type ID number. For example, Figure 1 shows Eagle Point Bridge in Dubuque, Iowa. The main spans are in the background, to the right are steel through trusses – the roadway goes through the trusses. The approach spans, in the left foreground, are steel Pratt deck trusses – the trusses are entirely underneath the roadway.

Table 2: Main Span Type Classifications

Classification	Subclassification
Cable-stayed	Concrete, steel
Cantilever	Warren or NULL
Covered	Burr arch, Howe, Lattice or NULL
Deck arch	Concrete, Concrete open spandrel, Steel, Stone
Deck truss	Bascule, Camelback, Howe, Lift, Parker, Pratt, Swing, Warren
Girder	Bascule, Concrete, Lift, Steel, Swing
Half-through arch	Concrete, Concrete open spandrel, Steel, Stone
Half-through truss	Bascule, Camelback, Howe, Lift, Parker, Pratt, Swing, Warren
Suspension	NULL
Through arch	Concrete, Concrete open spandrel, Steel
Through truss	Bascule, Camelback, Howe, Lift, Parker, Pennsylvania, Pratt, Swing, Warren

Fig. 1. Eagle Point Bridge, Dubuque IA, 1902 (HAER IA-2-56). (Image Source: https://www.loc.gov/resource/hhh.ia0114.photos/?sp=56&q=Eagle+Point+Bridge)

Each image is assigned a unique identifier and associated with the fields shown in Table 3. Each bridge is typically associated with more than one image. Rare images depict two or more distinct bridges.

Table 3: Fields to Define Images

Field	Contents
Photo ID (primary key)	Number
Bridge	Bridge ID (foreign key to Table 1)
Image Restriction	Public Domain or Restricted
Source URL	Wikipedia, Wikimedia Commons., or HAER

Computational Analysis

The compilation of the image database is accompanied by development of an automated system for analysing historical and contemporary images of bridges, depicted in Figure 2 and based on similar systems previously developed[1] for use by historians of technology.

'Ground truth' images that have been analysed by Bartlett are retrieved from the image database to use for testing and training. Test images can also be retrieved from other sources, typically collections built by web crawling. Creating a custom neural net that segments an image of a natural scene to identify general structures of interest requires a large collection of labelled image data that we do not possess. Instead, images are passed through an Ademxapp Model A1 neural net[2] that was pretrained with the ADE20K database of more than 20000 images[3] to segment scenes into semantic classes. A number of alternatives could have been applied at this stage, but this model does an excellent job and was readily available in pretrained form. Figure 3 shows a sample output where the system has quite accurately identified the Pierre Laporte suspension bridge in the foreground and the Pont de Quebec cantilever truss in the background. In a preliminary trial involving 100 images, the Ademxapp Model A1 correctly identified bridge elements in 83 of 84 images that contained bridges and correctly identified that no bridge elements were present in all 16 images that did not contain bridges.

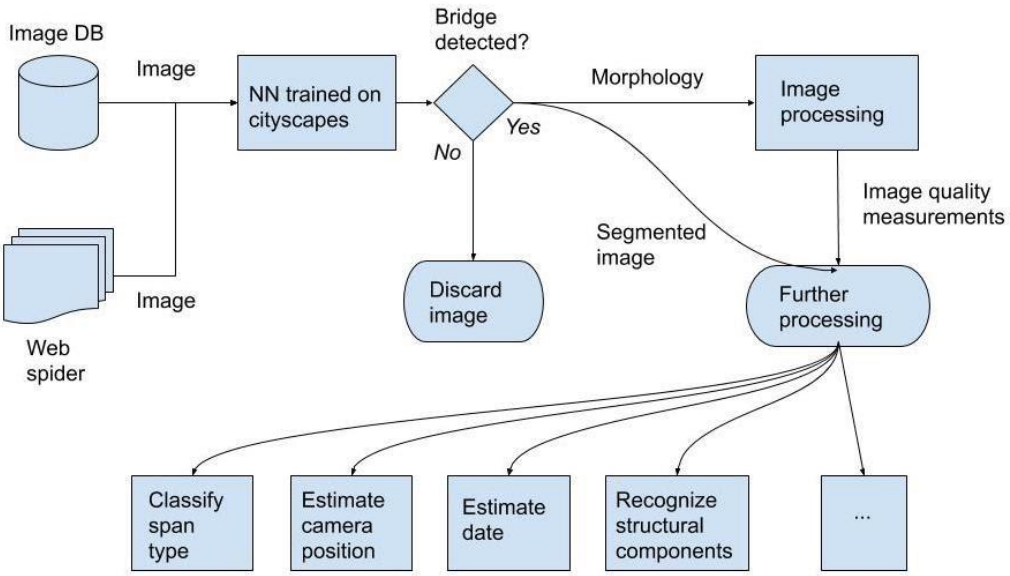

Fig. 2. Block diagram of an automated system for analyzing bridge images. (© W.J. Turkelt)

a *b*

Fig. 3. Machine vision identification of bridge and other features a) original image; b) identified features. (Image source: a) https://commons.wikimedia.org/wiki/File:LaPorte_de_Quebec_(5802230245).jpg, b) Created by W. J. Turkel using Ademxapp Model A1

If no bridge is detected in the input image, the image is discarded, and the system retrieves another. If a bridge has been detected, morphological information from the image is passed to an image processing module to assess the quality of the image for the purposes of further automated handling. The shape of the segment of the image that contains the bridge is measured to assess its orientation, how much of the whole image it comprises, and so on. These measures are used to determine what kinds of further automated processing are possible or appropriate.

Other machine learners (such as logistic regression models) have been trained to categorize bridge images by main span type, typically achieving accuracies upwards of 85%. For example, Figure 4 shows an example of using the artificial intelligence classifier to determine the main span type. The AI was trained using 80 images of through truss bridges, such as the elegant 1889 Lenticular through truss at Lycoming County, Pennsylvania, and 80 images of girder bridges, such as the 1940 Edison Bridge in New Jersey. Then it classified 168 new images as either girder bridges or through truss bridges. The screen shot indicates that the classification was almost 92% accurate as confirmed by the Confusion Matrix plot.

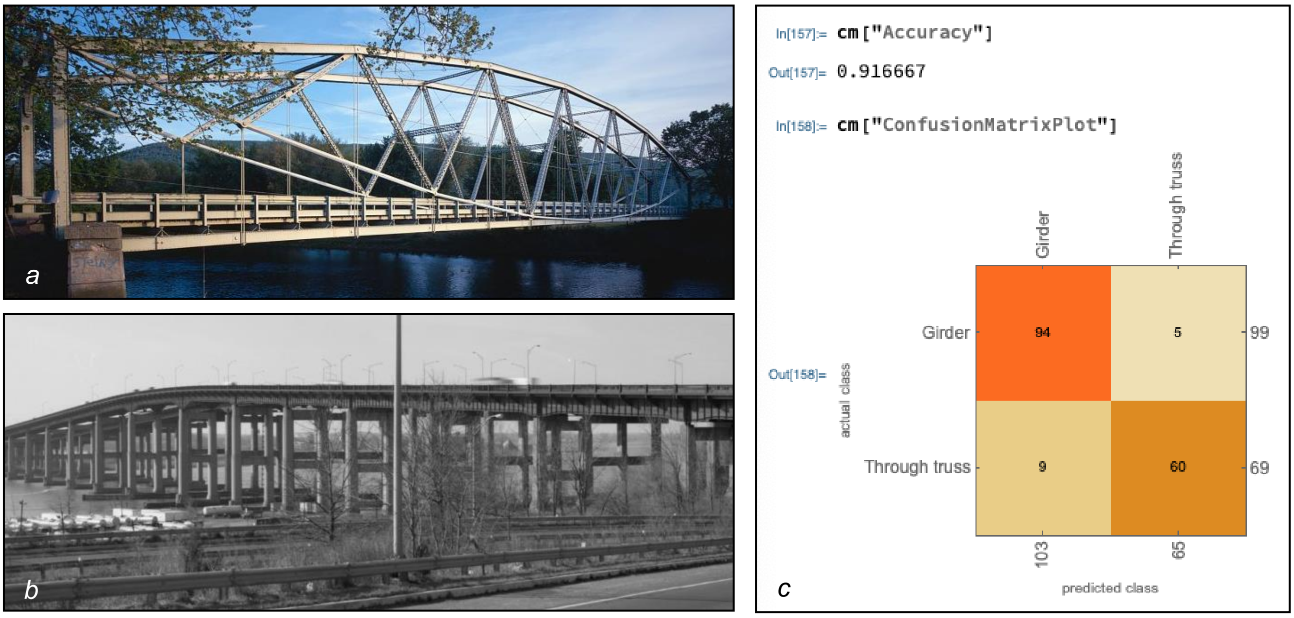

Fig. 4. AI classifier to determine bridge type: a) Lenticular Through Truss, Lycoming Co. PA, 1889 (HAER); b) Edison Bridge, Sayreville NJ, 1940 (HAER); c) screen shot of Mathematica Confusion Matrix and accuracy. (Image sources: a) https://www.loc.gov/pictures/item/pa3981.color.218398c/resource/ b) https://www.loc.gov/pictures/item/nj1641.photos.347596p/ c) Created by W. J. Turkel using Mathematica.)

Figure 5 shows an example where the classification was extended to consider five different types, including cantilever, deck arch, girder, through arch and through truss bridges. In this case, the accuracy was not so good, roughly 69%. Looking more closely at the confusion matrix there were no girder bridges that were erroneously classified as through arches, which is not surprising as they are markedly different forms. There were, however, cantilevers erroneously classified as deck arches and deck arches erroneously classified as cantilevers. In this case, one might have some sympathy for the computer! Compare, for example, the 1932 French King Bridge in Gill, Massachusetts, a steel cantilever bridge, with the 1928 Gervais Creek Bridge in South Carolina, a deck arch bridge. The cantilever has diagonal members in the trusses and the deck truss has thick vertical members over the piers – but otherwise, their appearances are not particularly different.

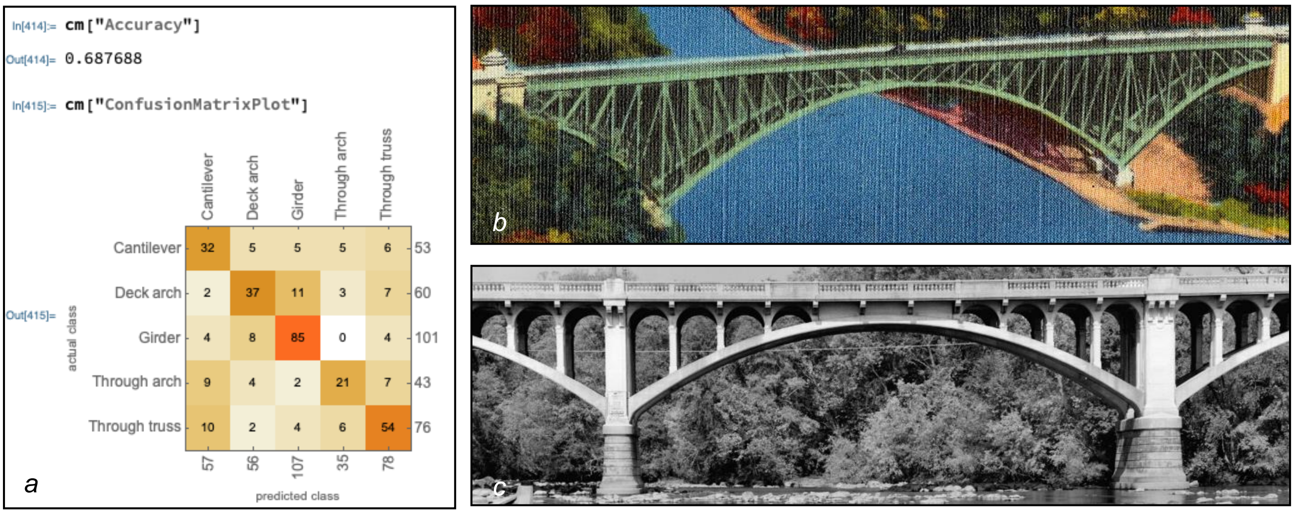

Fig. 5. AI classifier to determine multiple bridge types: a) screen shot of Mathematica Confusion Matrix and accuracy; b) French King Bridge, Gill MA, 1932 (Commons.wikimedia.org); c) Gervais Creek Bridge, Columbia SC, 1928 (HAER) (Image Source: a) Created by W. J. Turkel using Mathematica b) https://www.digitalcommonwealth.org/search/commonwealth:6d5701630 c) https://www.loc.gov/pictures/item/sc0757.photos.150689p/)

Future work will focus on developing machine learners for a variety of automated tasks. One example is the automated recognition of structural components like truss type. Figure 6 shows Pratt (horizontal top chord), Parker (polygonal top chord) and Camelback (5-element top chord) trusses.

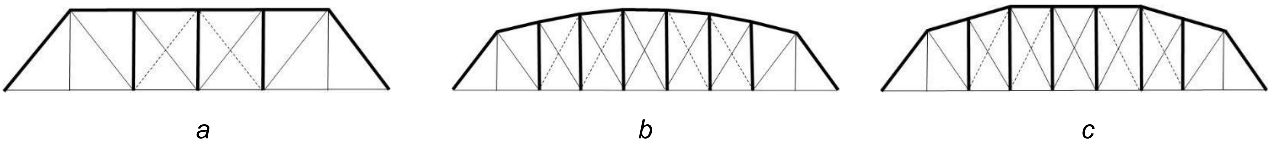

Fig. 6. Truss configurations a) Pratt; b) Parker; c) Camelback. (HAER) (Created by F. M. Bartlett)

Another example is estimating the date of bridge construction. 'Black-box' machine learners perform this task using features that are usually not legible to humans. Human experts, on the other hand, use a variety of construction details, including the examples shown in Table 4. Developing the database in conjunction with an automated system for analysing bridge images allows researchers to explore the degree to which the system should be trained to explicitly recognize construction details (like the use of pin-connected or riveted trusses). This is challenging, however, time is a continuum, so the classification must consider the shades of grey between black and white.

Table 4: Evolution of Bridge Construction Details.

Date	Feature
~1875	Emergence of double-intersection trusses
~1880	Transition from empirical to theoretical bridge design completed in US4
~1890	Emergence of steel construction instead of wrought/cast iron construction
~1900	Emergence of plain and reinforced concrete (piers, abutments, superstructure)
~1910	Milan theory of earth-anchored suspension bridges causes markedly more slender stiffening elements.
~1910	Emergence of concrete tied arch ("rainbow") bridges and concrete open spandrel deck arch bridges
~1920	Emergence of riveted trusses instead of pin-connected trusses
~1930	Emergence of rigid frame construction
~1950	Emergence of prestressed concrete construction
~1950	Transition from built-up steel members to single rolled shapes
~1980	Emergence of cable-stayed bridges instead of cantilever trusses

Moreover, some types have not evolved much. The 377 images of wooden covered bridges in the database suggest that their form and construction details have often not changed appreciably for over a century. People are nostalgic about the traditional forms. Similarly, the optimization of steel Pratt trusses was essentially completed more than a century ago, so while construction details change, the general proportions and member massing do not. Another challenge is that technological progress varies across geographical regions, and progress for different bridge types typically varies differently across different geographical regions.

Some transitions are more difficult to date, for example

- The transitions from pin-connected to riveted to shop-riveted/field-bolted to shop-welded/field bolted to welded steel construction. For example, Figure 7a shows the 1891 Harvard Bridge across the Charles River in Boston. The variable-depth steel plate girders are built up using rivets. When the bridge was replaced in the 1980s with similar variable-depth plate girders, the construction is welded, not riveted.


a b

Fig. 7. Harvard Bridge plate girders a) Riveted construction, 1891 (Source: HAER); b) Welded construction, 1980s (Image source a) https://www.loc.gov/pictures/item/ma1293.photos.076534p/resource/ b) Denimadept, CC BY-SA 3.0 https://creativecommons.org/licenses/by-sa/3.0, via Wikimedia Commons)

- The transition to more slender, and so more graceful, elements and structures due to stronger and stiffer materials.
- The transition to more complex geometries and structural systems due to enhanced computational capabilities. This is particularly evident in the design of cable-stayed bridges. Figure 8a shows the 1973 John O'Carroll Bridge in Sitka, AL, one of the first cable-stayed bridges constructed in the United States. There are a total of eight cables in the two vertical planes. It is statically indeterminate to the 4th degree – that means that four equations of deflection compatibility must be added to the equations of equilibrium to analyse the structure. In contrast, Figure 8b shows the 2012 Margaret Hunt Hill Bridge in Dallas, TX, designed by Santiago Calatrava. It has a much more complex geometry, with 58 cables arranged in surfaces that resemble hyperbolic paraboloids, and the degree of indeterminacy is beyond simple calculation. Powerful 3-Dimensional structural analysis programs are necessary to demonstrate that this structure can successfully resist the loads that it carries.


a b

Fig. 8. Evolution of cable-stayed bridges a) John O'Connell Bridge, Sitka AK, 1973 (Source: Wikipedia); b) Margaret Hunt Hill Bridge, Dallas TX, 2012 (Image source a) https://commons.wikimedia.org/wiki/File:John_O%27Connell_Bridge,_Sitka_2013.JPG b) Michael Barera, CC BY-SA 4.0 https://creativecommons.org/licenses/by-sa/4.0, via Wikimedia Commons)

- The impact of the increased labour costs: fewer built-up steel members, more precast concrete construction and the use of concrete instead of masonry in towers, piers and foundations.

A final example of a task that is currently being automated is to use image processing and photogrammetric techniques to try to identify the vantage point from which the bridge was photographed. Others[5] identified five specific vantage points that are important for viewing bridges, “(a) travelling over the bridge at slow speed; (b) travelling over the bridge at high speed; (c) travelling under the bridge at slow speed (d); travelling under the bridge at high speed; and (e) viewing the bridge from a distance.” Successfully estimating camera position with respect to the bridge will be useful for more sophisticated image understanding tasks.

Summary

This short paper has summarized work-in-progress to create a database of 4800 electronic images of historic American and Canadian highway, railway and pedestrian bridges constructed between 1865 and 2019, retrieved from Wikipedia, Wikimedia Commons, and the Historic American Engineering Record (HAER) websites. These images are being used concurrently to develop machine-vision systems and image-processing techniques to automatically identify, in historical and contemporary images of cityscapes and landscapes: (1) the presence of a bridge or bridge component in an image; (2) the form (or type) of bridge or bridge component; (3) the age and other features; and (4) the vantage point from which the bridge was photographed. The Artificial Intelligence classification identifier was 85–92% accurate when distinguishing between girder and through-truss bridge types and roughly 70% accurate when distinguishing between cantilever, through-arch, girder, through-truss and deck arch bridges types. It is perhaps more challenging to determine the date of construction because time is a continuum: the evolution of bridge types and construction details is somewhat blurry and varies between different geographic regions. A possible next step will be to use image-processing and photogrammetric techniques to try to identify the vantage point from which the bridge was photographed. The relevance of this study extends beyond those interested in historic bridges to scholars studying image classification in other areas of the digital humanities.

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Conceptualization: F. M. Bartlett and W. J. Turkel
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Project Administration: F. M. Bartlett and W. J. Turkel
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Visualization: F. M. Bartlett and W. J. Turkel
Writing – original draft: F. M. Bartlett and W. J. Turkel
Writing – review & editing: W. J. Turkel and F. M. Bartlett

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