# Façade Inspection Comparative Study: Binocular, Close-up, and AI-assisted

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Fig. 1: Centrepoint East North Building

Fig. 2: Centrepoint East South Building

The Centrepoint East buildings are two residential mid-century modern high-rises in Toronto, Canada, recognized as examples of brutalist architecture by the Architectural Conservancy Ontario (ACO), although not currently listed as historic buildings. Alongside an effort to upgrade the energy efficiency of the buildings, numerous unsafe spalls and cracks were observed on the concrete façades, leading to the opportunity to use an artificial intelligence-based screening tool, combined with a binocular and close-up inspection, to understand the extent of the conditions.

The taller North (Fig. 1) and shorter South Building (Fig. 2) of the Centrepoint East complex were designed by Ryan and Lee Architects and built in 1974. Connected by a concrete park with welded bronze sculptures by Krystyna Sadowska (1967), the buildings are a statement of the architects' attempt to follow Le Corbusier's Five Points of Architecture within the economic restraints they faced.

The building façades typically comprise architecturally exposed concrete, masonry knee walls, and ribbon windows. Each unit has a balcony, consisting of an extension of the concrete floor plate and concrete fin walls on the sides. As part of thermal efficiency improvements to the buildings, the façades were to receive overcladding at the brick knee walls and associated concrete slabs. However, prior to the alteration, the concrete façades needed to undergo a comprehensive examination and restoration program. The envelope renewal program included concrete and crack repairs to the concrete façades, balcony slabs, parapets, roof ornamentation, and a protective coating at the repaired exterior walls.

To determine the quantities of cracks and spalls, an initial binocular inspection of all areas of the façades was performed. The conditions were documented with photos using a hand-held digital camera. Multiple instances of concrete spalls, cracks and exposed rebar were observed, which necessitated further investigation via hands-on inspection from a suspended scaffold.

## FAÇADE INSPECTION STUDY

As capable image-based sensing systems become more abundant and artificial intelligence techniques become more advanced, they provide an opportunity to collect high resolution images and make smart predictions on these images. Compared to traditional façade inspections, AI-assisted façade inspection promises increased inspection flexibility and efficiency, while reducing human error and inspection time. In order to confirm the observations and quantities, an AI-based application was used to perform a comparative study of efficiency between conventional and AI-assisted façade surveys.

The aim of the study was to evaluate both conventional and AI-assisted façade inspections and identify the most efficient and accurate way of façade inspection, data collection and evaluation, considering the following factors:

- Ease of calculating accurate quantities for future pricing of repair work; and
- Involvement of inspection staff and the corresponding time and cost.

### Methodology

The study compared results of three types of visual façade inspections: binocular inspection and close-up inspection from scaffolds, which were analyzed manually, and AI-assisted inspection, performed on photographs collected during the close-up inspection, analyzed by an AI-based application.

#### *Binocular*

Visual examination of all viewable façades was performed from the street and backyard, using 8x zoom binoculars. Observations were manually marked on elevation drawing printouts, and then transferred into Building Information Modeling (BIM) in further phases of the project.

#### *Visual Close-up*

Visual close-up inspections were performed on the entire façade via 52 suspended scaffold drops and manually marked on elevation drawing printouts. The time specified for this survey was one hour per scaffold drop for each employee, not including commute time.

#### *AI-assisted*

The application utilized in this test used computer vision—a narrow form of artificial intelligence built with deep learning—to automatically detect and localize façade deterioration by analyzing photographic images or drone footage. It can be deployed as a mobile app or via a web-based interface.

The app used deep convolution neural networks for image classification and object detection built on frameworks for machine learning. It was trained extensively on project images collected over many years of building investigations and repairs. Under its hood, it consists of multiple modules to enhance detections including:

- A structural segmentation tool that identifies the structure relative to its background;
- A proximity classifier that determines if the image is taken at a close-in or a wide-angle range;
- A material classifier that identifies the type of substrate material; and
- Multiple damage detection models for different substrate materials (these material-specific damage detection models can identify various damage condition types across different material substrates, such as cracks and spalls for concrete structures required in this survey).

### Dataset

The datasets were tested using a concrete-specific machine learning model trained on thousands of images showing concrete conditions. Images used for the AI test were collected during the close-up inspection described below.

The selected datasets (drops A, B and drops C, D, E, F) were prepared by two inspectors and were varied in terms of building components and image counts, as described in Table 1.

**Table 1: Dataset Characteristics**

| Dataset | Image Count | Building Area |
|---|---|---|
| A, B | 110 | Architectural concrete wall |
| C, D, E, F | 1204 | Concrete slab edge, brick veneer knee wall, architectural concrete balcony side walls |

### Results and Discussion

The case study was performed on two datasets, including two (A, B) and four (C, D, E, F) scaffold drops, respectively. See Tables 2 and 3 for comparison of achieved results.

**Table 2: Inspection Results on Drops A and B**

| Scaffold Drops A, B | | | |
|---|---|---|---|
| *Type of Inspection* | *Number of cracks (percentage of close-up quantity)* | *Number of spalls (percentage of close-up quantity)* | *Number of exposed rebars (percentage of close-up quantity)* |
| Binocular | 3 (4%) | 27 (25%) | - (0%) |
| AI-assisted | 51 (75%) | 129 (121%) | 38 (88%) |
| AI-assisted inspection after manual adjustment | 62 (91%) | 98 (92%) | 36 (84%) |
| Visual close-up | 68 | 106 | 43 |

**Table 3: Inspection Results on Drops C, D, E, and F**

| Scaffold Drops C, D, E, F | | | |
|---|---|---|---|
| *Type of Inspection* | *Number of cracks (percentage of close-up quantity)* | *Number of spalls (percentage of close-up quantity)* | *Number of exposed rebars (percentage of close-up quantity)* |
| Binocular | 6 (10%) | 22 (10%) | 1 (10%) |
| AI-assisted | 375 (614%) | 188 (88%) | 546 (5460%) |
| AI-assisted inspection after manual adjustment | 214 (350%) | 278 (130%) | 39 (390%) |
| Visual close-up | 61 | 213 | 10 |

Fig. 3: False positive indication—lifeline detected as exposed rebar

Dataset "A, B" included photos of architecturally exposed concrete. There were three examples of errors which required manual enhancement:

- Multiple photos showing the same condition at a different angle due to the photos being manually taken with a digital camera. In the post-production process (described further as manual adjustment), doubled photographs were removed;
- Lifeline detected as exposed rebar. Most likely due to the shape of lifeline, there were several instances where it was detected as exposed rebar; and
- Spalls which exposed rebar showed double detections in several cases. Although not necessarily a wrong indication, this was manually adjusted to show spalls in deeper conditions and exposed rebar in more shallow, smaller conditions.

Dataset "C, D, E, F" consisted of some areas of brick veneer, which caused an additional false positive indication. Some areas of brick were detected as rebar. This false positive indication may have been caused by the color of brick being similar to the exposed rebar in other locations.

Fig. 4: Double positive indication—spall and exposed rebar

Fig. 5: Example of AI condition detection (red boxes display detected exposed rebar, green—spall, yellow—crack)

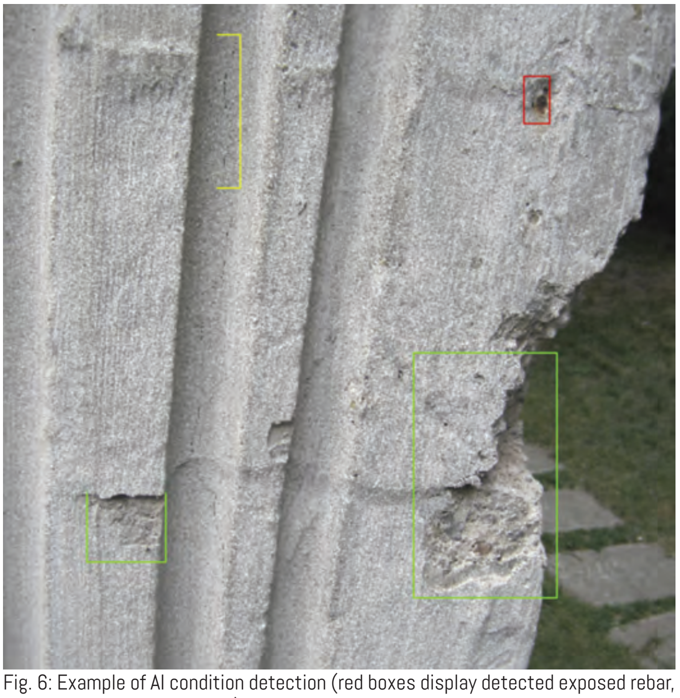

Fig. 6: Example of AI condition detection (red boxes display detected exposed rebar, green—spall, yellow—crack).

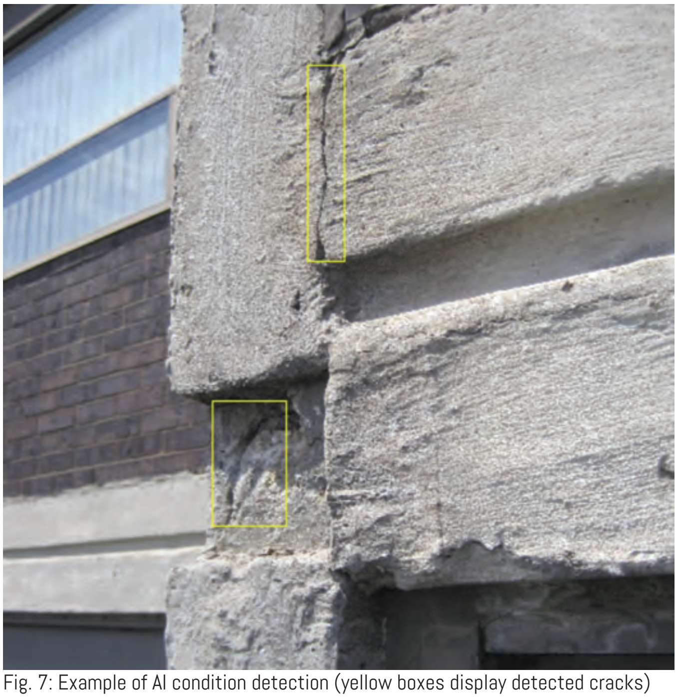

Fig. 7: Example of AI condition detection (yellow boxes display detected cracks)

**Table 4: Combined Inspection Results**

| Scaffold Drops A, B, C, D, E, F | | | |
|---|---|---|---|
| *Type of Inspection* | *Number of cracks (percentage of close-up quantity)* | *Number of spalls (percentage of close-up quantity)* | *Number of exposed rebars (percentage of close-up quantity)* |
| Binocular | 9 (7%) | 49 (15%) | 1 (2%) |
| AI-assisted inspection after manual adjustment | 276 (214%) | 376 (118%) | 75 (142%) |
| Visual close-up | 129 | 319 | 53 |

The total count of AI-assisted condition count was approximately 150 percent of the conditions mapped manually during close-up inspections (refer to Table 4). This is most likely due to a number of hairline shrinkage cracks which were not mapped by the inspector, and other minor conditions.

## CONCLUSIONS

This case study shows that computational techniques such as the AI-based façade condition detector can reduce the time of a visual survey by over 90 percent and be very useful in rapid and accurate repair work budget projections for clients. The use of AI technology presents the construction industry with an opportunity to significantly reduce time of initial inspections (refer to Table 5) and increase the accuracy of condition quantity forecasts.

When combined with drone data collection, this AI-based tool eliminates the need to engage a contractor for close-up access for the investigation, such as supported or suspended scaffolding. This reduces the time the scaffold is installed on the building to only the repair phase, which will be appreciated by both owners and occupants.

An additional benefit of using the computational method supported by drone data collection is the possibility to automatically generate drawings showing the locations of detected conditions. The additional time needed to transfer hand sketches into CAD drawings or BIM was not included in this study.

**Table 5: Summary of Extrapolated Time Expenditure during Each of the Inspections**

| Type of Inspection | Time Spent (person-hours) for 6 Drops | Time Spent (person-hours) for Two Buildings (52 drops) - Extrapolation |
|---|---|---|
| Binocular | 1 hour | 9 hours |
| AI-assisted | 1 hour | 4 hours of drone data gathering and less than 1 hour of app use* |
| Visual close-up | 6 hours** | 70 hours over 3 months |

* Two drone operators are required

** Plus additional cost of engaging an external contractor to install suspended scaffolding, and associated man-hours of motor operators / riggers accompanying the inspector on a drop

Drone use would facilitate the geo-localization module of the app, which maps detected damage to associated locations on the structure. The location, altitude, and orientation data would be obtained from drone localization and presented to users on a dashboard. This module minimizes the time and cost spent on post-production of condition mapping in CAD or BIM.

Furthermore, at this stage of development of the app, some extent of manual adjustment of results was required. The app utilizes reinforcement learning to improve the framework continuously with the feedback coming from the users, which ensures better results in the future.

Based on this study, AI-assisted surveys provide more reliable assessment data than binocular inspections on some buildings. They can be faster and less expensive than conventional close-up inspections, while rapidly providing reports and drawings.

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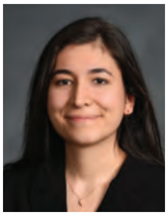

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