# Automated Detection and Quantification of Cracks and Spalls in Concrete Bridge Decks Using Deep Learning


Qianyun. Zhang [1] and Amir. H. Alavi [2]

1. PhD Student, Department of Civil & Environmental Engineering, University of Pittsburgh, Email: qiz89@pitt.edu

2. Assistant Professor, Department of Civil & Environmental Engineering, University of Pittsburgh, Email: alavi@pitt.edu


## Introduction

Challenges in manual concrete deck surface inspections


Periodic inspection and evaluation are national requirements for bridge decks.

## Problem Statement

Limitations of current vision-based methods

- Image processing techniques
  - highly dependent on manually parameter tuning
- Deep learning methods
  - Smooth concrete surfaces

## Objectives

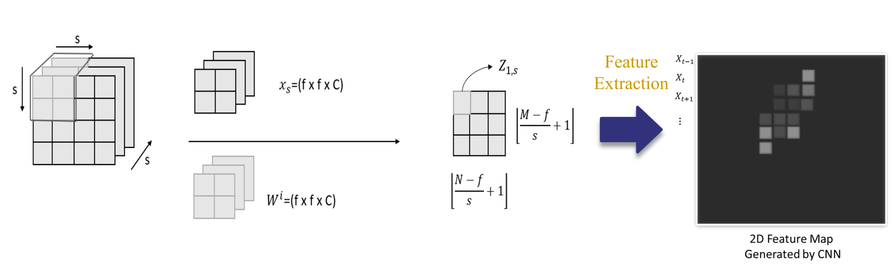
This study is going to proposed a vision-based method for crack and spall detection that is:

- Automatic
- Accurate
- Qualitative
- Quantitative

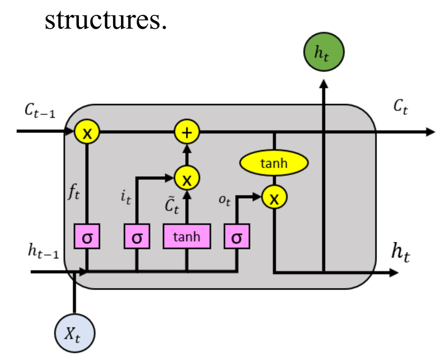
## Methodology

A hybrid deep learning method combining convolution neural networks (CNN) and long short term memory (LSTM), called CNN-LSTM, for the detection and quantification of concrete bridge deck surface defects is proposed.

- Convolution Neural Network (CNN)
  - CNN is the most well-known deep learning architecture that is capable to extract extracting higher level features from the raw data.
  - Convolutional layers apply a number of filters to the local regions of inputs to extract feature maps of the images.

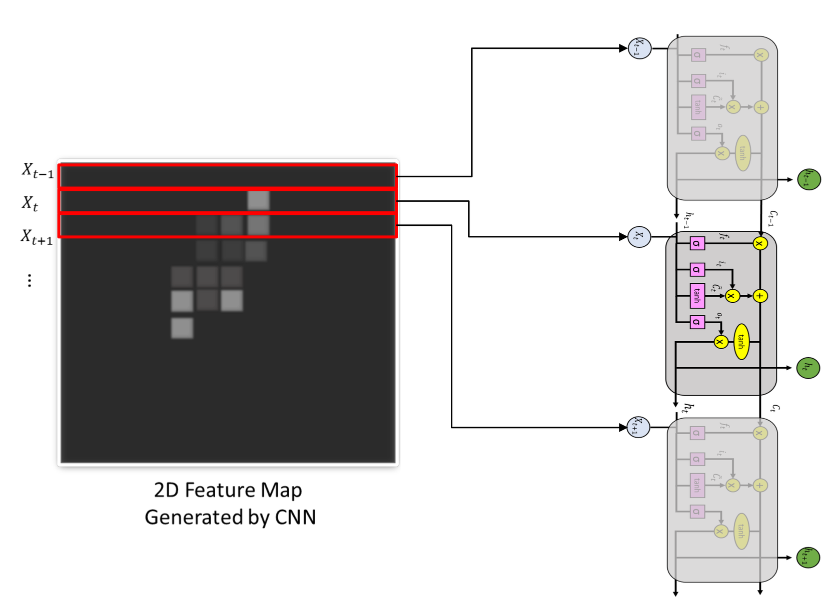



- Long Short Term Memory (LSTM)
  - LSTM is an invariant of recurrent neural networks that works for sequential data.
  - It is capable to selectively forget input features by three threshold structures.



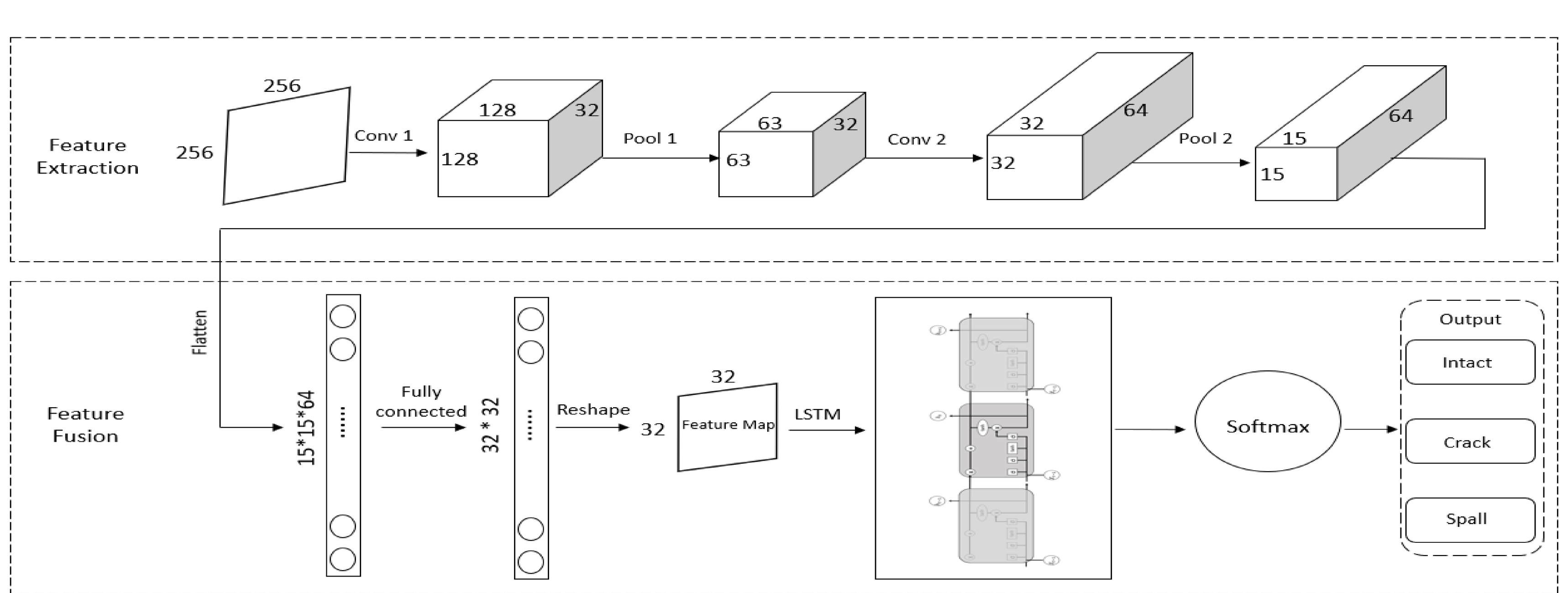
$$f_t = \sigma(W_f[h_{t-1}, X_t] + b_f)$$
$$i_t = \sigma(W_i[h_{t-1}, X_t] + b_i)$$
$$\tilde{C}_t = \tanh(W_c[h_{t-1}, X_t] + b_c)$$
$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$
$$o_t = \sigma(W_o[h_{t-1}, X_t] + b_o)$$
$$h_t = o_t * \tanh(C_t)$$

- CNN-LSTM
  - During the feature extraction stage, keep the filter window size always larger than stride size, there are overlaps of each step. This makes extracted feature blocks are strongly dependent on each other.
  - Extracted feature map can be reshaped to 2D map matrix, and each row of the matrix can be regarded as one input.
  - All rows of the feature map can be regarded as sequential input data to be passed to LSTM for feature fusion.



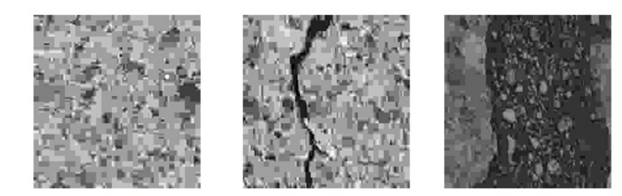
2D Feature Map Generated by CNN

- Network Architecture

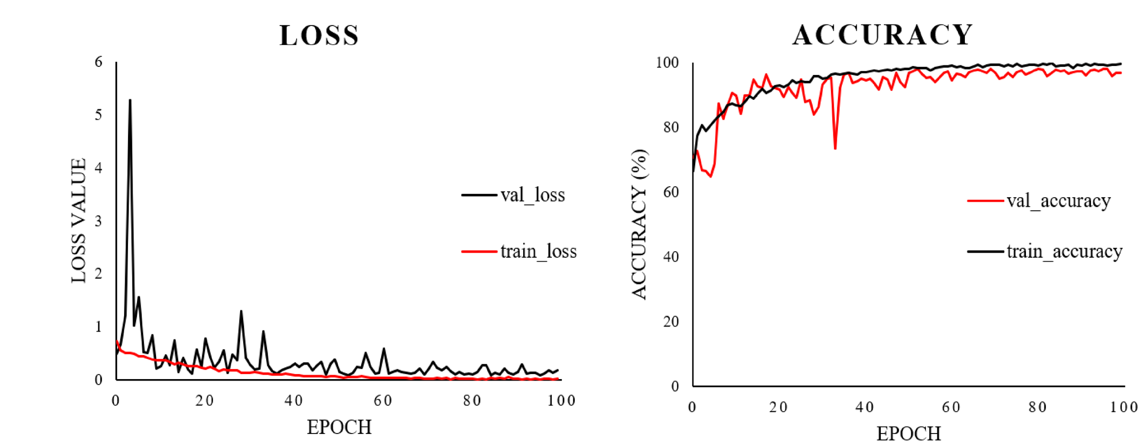



## Database and Model Training

- Database
- Images from rough concrete pavements located in Pittsburgh, PA are collected in this study.
- 7200 images with size 256 ×256 pixels are used in this study.
- Images are manually categorized into 3 classes: intact, cracking, spalling.

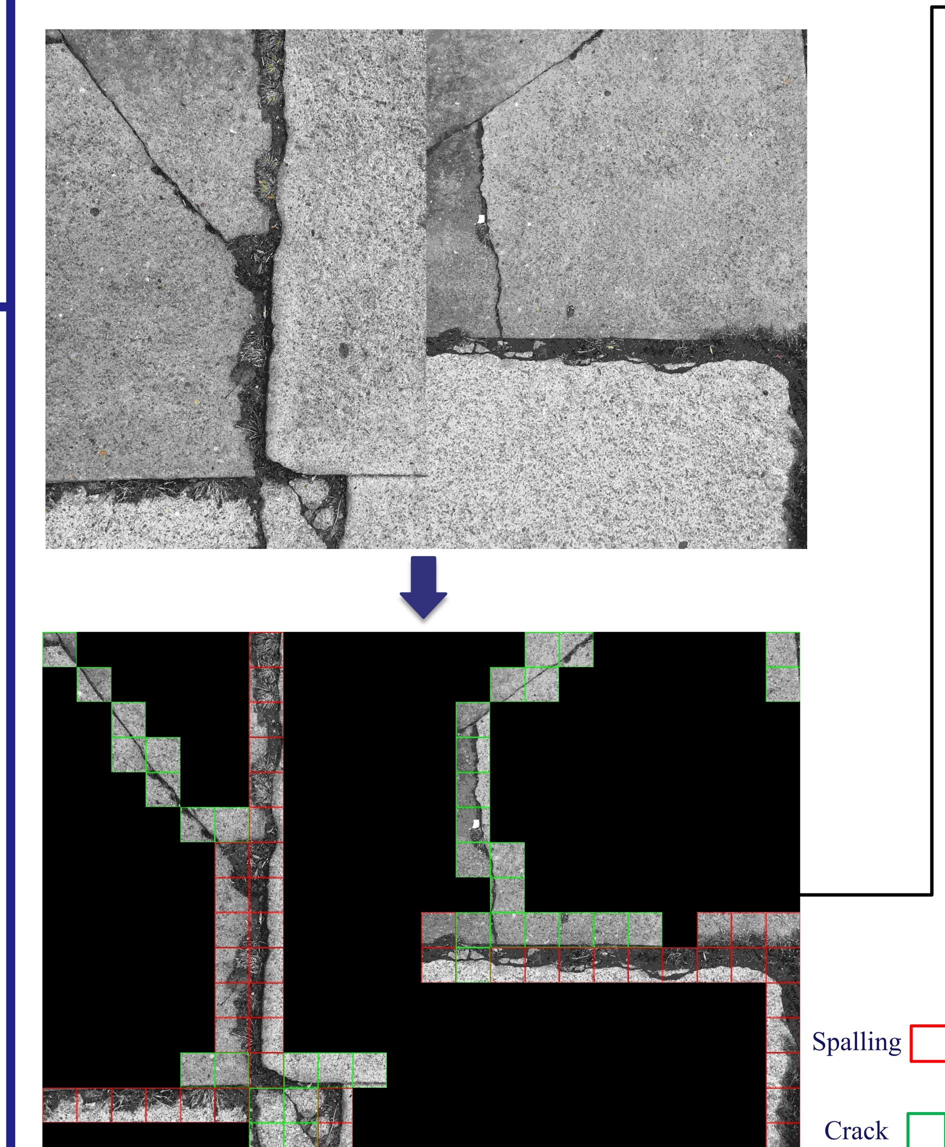


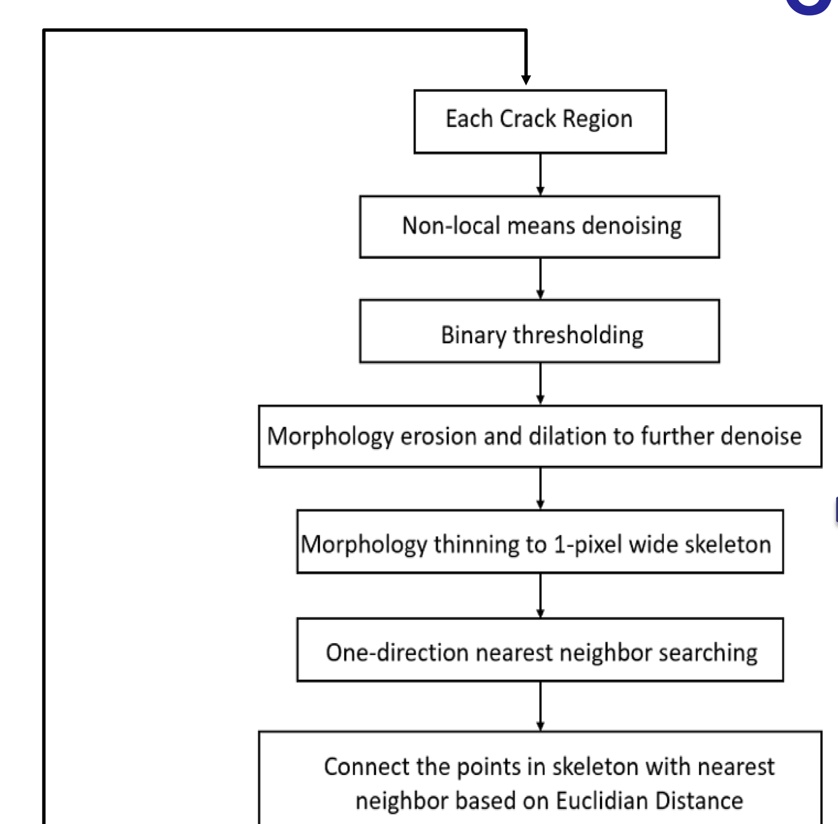

- Training Results



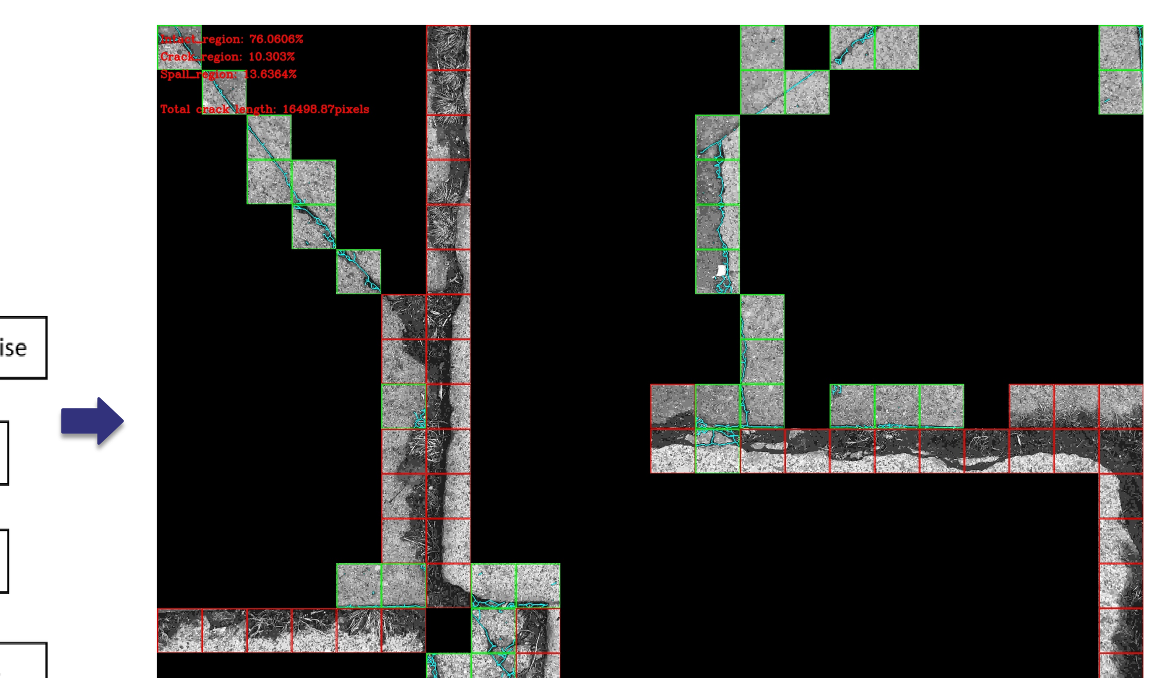

Accuracy of training and validation are 99.7% and 98.64%

## Model Implementation




## Crack Length Quantification



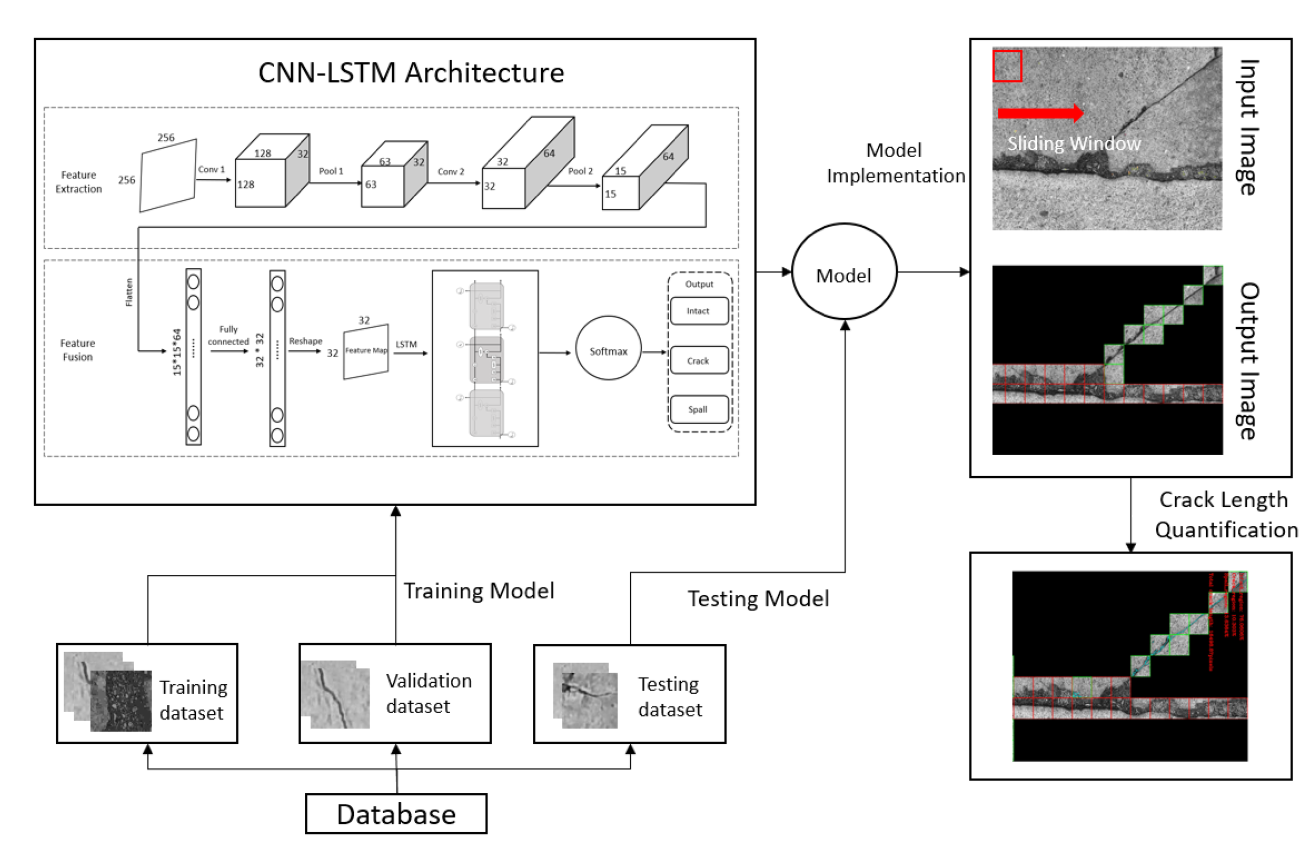
Crack — Crack Region Spalling Region

$$Crack\ Region\ (\%) = \frac{Number\ of\ local\ window\ with\ crack}{Total\ number\ of\ local\ windows} * 100$$

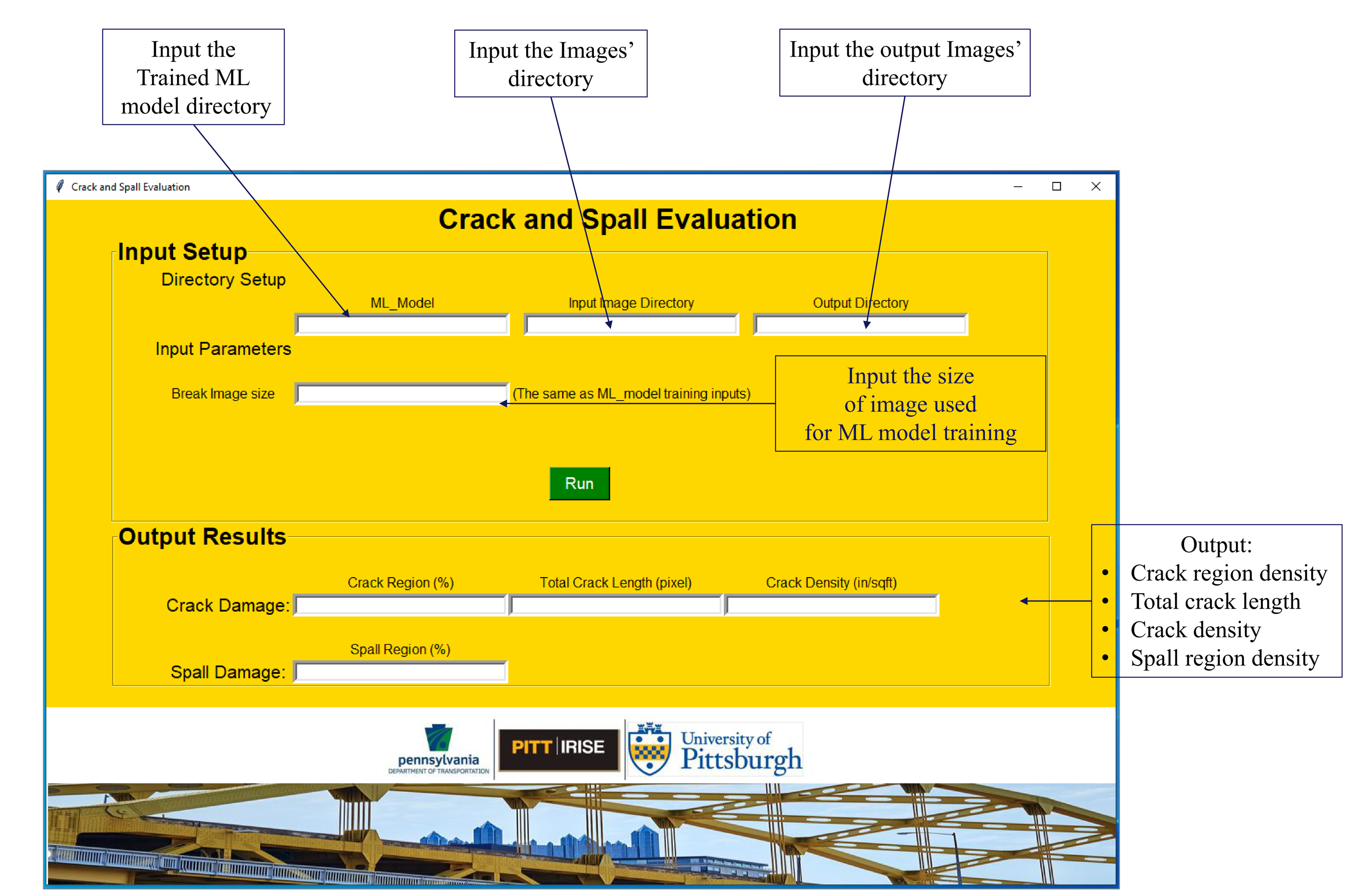
$$Crack\ Density = \frac{Total\ Crack\ Length}{Total\ Inspection\ Area} * 100$$

$$Spall\ Region\ (\%) = \frac{Number\ of\ local\ window\ with\ spall}{Total\ number\ of\ local\ windows} * 100$$

## Framework and GUI




- Overall Framework




- Developed GUI