University of Pittsburgh

# Crack Image Segmentation

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# Overview

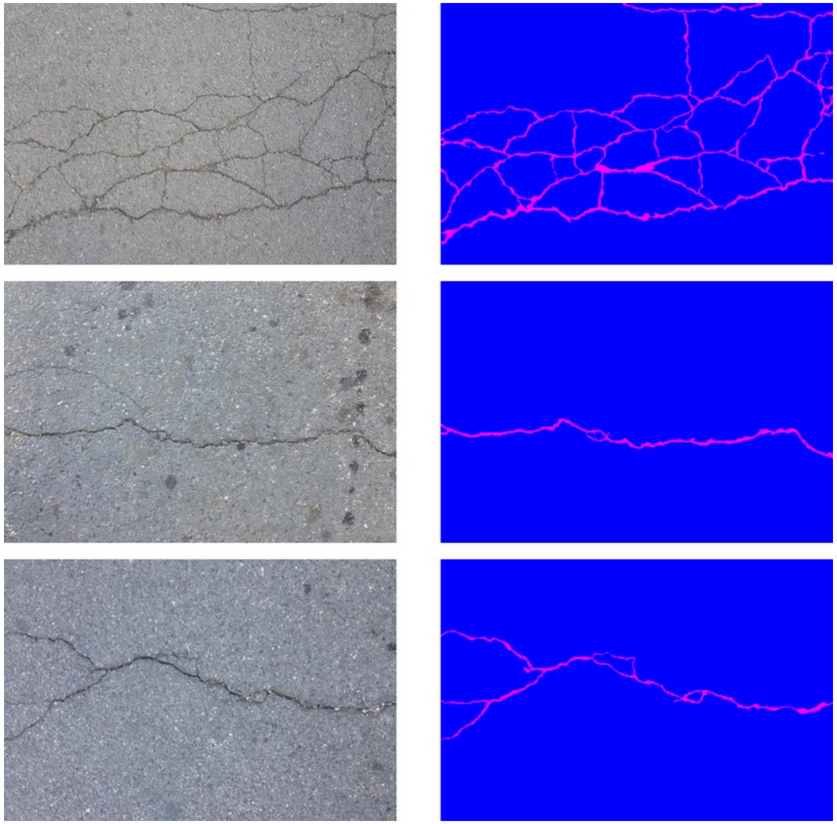
- Background
- Objective
- Literature Survey
- Proposed Method
  - Architecture
  - Metrics
- Results
- Future Work
- Conclusion

# Introduction

- Importance of road safety
- Challenges posed by road cracks
- Significance of image segmentation in addressing road safety issues

# Objective

The primary objective is to automatically and accurately detect the presence and location of road cracks, aiding in maintenance and safety.



# Traditional Road Inspections

- Manual inspection challenges
- Time-consuming processes
- Limited coverage and accuracy

# Advent & Role of Computer Vision

- Thresholding and Morphological Operations
- Edge Detection
- Texture Analysis

# Advent & Role of Computer Vision

Thresholding

- "Automatic Crack Detection on Concrete Structures Using 2D Gabor Filters" by M. Attari, et al. (2012) proposes crack detection using Gabor filters and thresholding.
- "A Review on Automatic Crack Detection Techniques" by S. Gautam, et al. (2018) provides an overview of various crack detection techniques, including thresholding.

# Advent & Role of Computer Vision

## Edge Detection

- "Crack Detection and Classification Based on Multi-feature Fusion" by C. Zhang, et al. (2019) introduces a crack detection method based on edge detection and feature fusion.
- "Crack Detection in Concrete Surfaces Using Convolutional Neural Networks" by L. Magalhães, et al. (2017) applies edge detection as part of a CNN-based crack detection approach

# Advent & Role of Computer Vision

## Texture Analysis

- "Concrete Crack Identification Using Adaptive Gabor Filter" by K. Noh, et al. (2017) proposes crack identification based on adaptive Gabor filtering for texture analysis.
- "Concrete Crack Detection Using Local Binary Patterns" by D. Luo, et al. (2018) utilizes local binary patterns for crack detection in concrete surfaces.

# Machine Learning

- Traditional Machine Learning
  - Random Forest,
  - SVM

# Machine Learning

1. **Title: "Road Crack Detection Using Random Forest and Image Segmentation"**
   1. Authors: D. Roy, M. Rahman, F. M. Abdullah
   2. Published in: 2017 IEEE Calcutta Conference (CALCON)
2. **Title: "Crack Detection in Images of Concrete Structures Using Genetic Algorithm and Support Vector Machines"**
   1. Authors: M. R. Asmael, J. M. Shata, A. I. Fahmy
   2. Published in: Procedia Computer Science, 2017

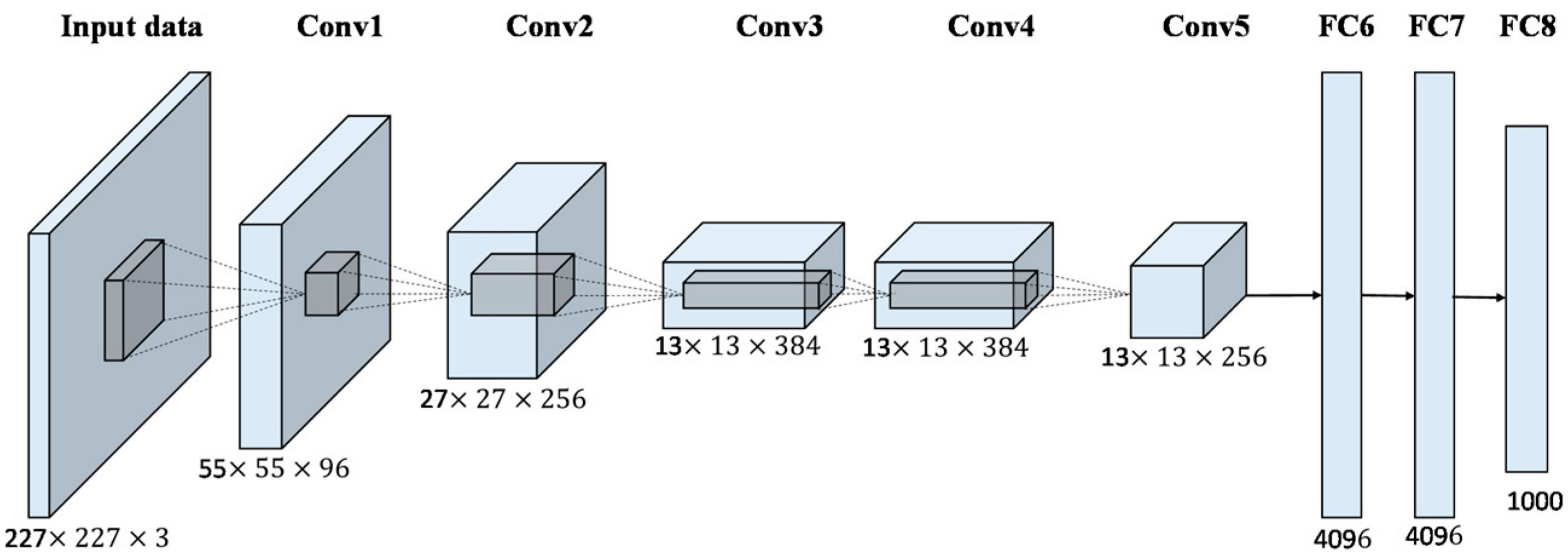
# Machine Learning

## 3. Title: "Road Crack Detection Using a Fuzzy Possibilistic Model and a Genetic Algorithm"

1. Authors: M. R. Asmael, J. M. Shata, A. I. Fahmy
2. Published in: Procedia Computer Science, 2017

# Advent of Deep Learning

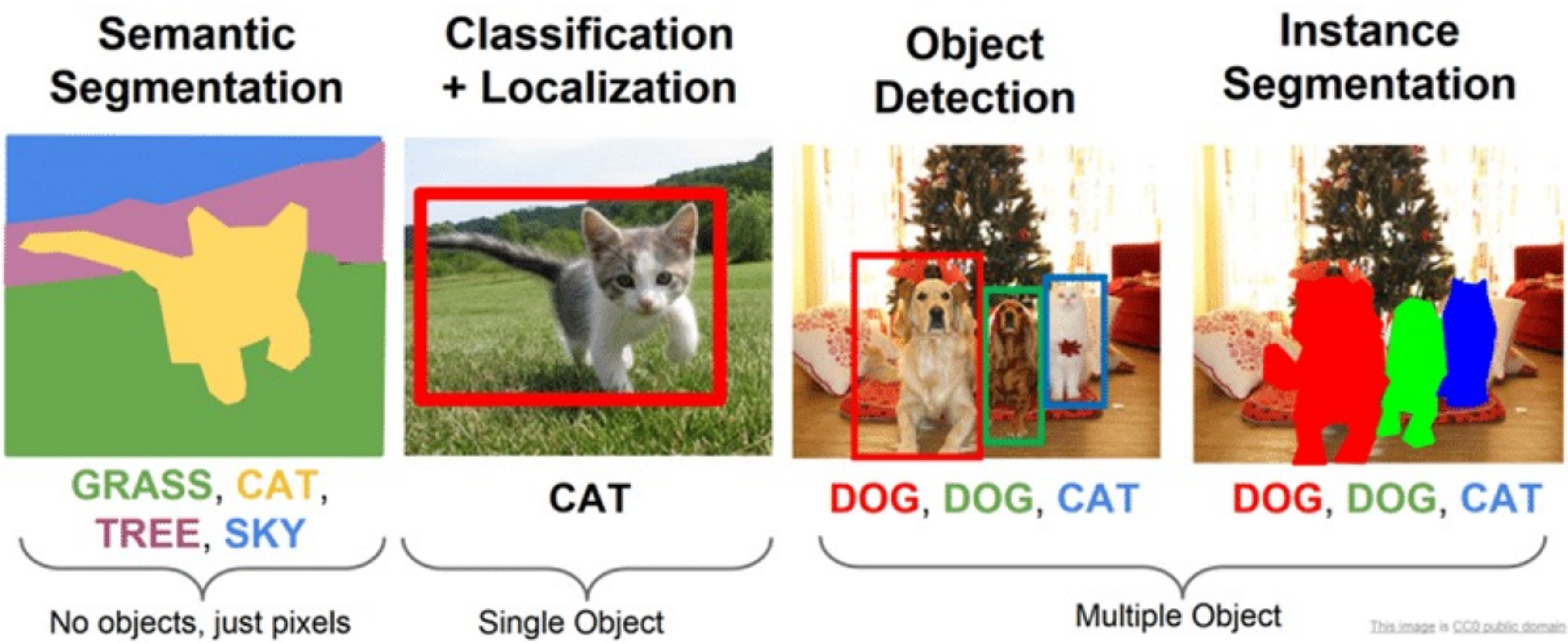
- Convolutional Neural Network (CNN):



# Advent of Deep Learning

- Convolutional Neural Network (CNN):
  - Classification
  - Object Detection
  - Pixel Level Image Segmentation

# Image Segmentation



# Advent of Deep Learning

## Classification:

- In “Large-scale continual road inspection: Visual infrastructure assessment in the wild” the author developed a deep learning method for road detection and evaluation based on convolutional neural network, Fisher vector coding, and UnderBagging random forest.
- In “Automatic detection method of cracks from concrete surface imagery using two-step light gradient boosting machine” the author proposed the use of Light Gradient Boosting Machine model for automatic crack detection and compare the results with pix2pix-based approach
- In “Road crack detection using deep convolutional neural network” the author proposed a six-layer CNN network with four convolutional layers and two fully connected layers to show that deep CNNs are superior to traditional machine learning techniques, such as SVM and boosting methods, in detecting pavement cracks.

# Advent of Deep Learning

## Object Detection:

- In “automatic surface crack detection using segmentation-based deep-learning approach ” uses 3 modules, Base architecture, Objectness Score Identification (OSI) Network and Region of Interest (ROI) pooling to first detect and then classify the cracks.
- Another paper adopted the modified ZF-net as the CNN feature extractor of Faster R-CNN. This helped in accelerating the process of feature extraction and was more suitable for real-time detection.

# Advent of Deep Learning

## Pixel level Image Segmentation:

- One paper proposed an end-to-end deep convolutional neural network (DeepCrack) to realize the automatic detection of cracks by learning high-level characteristics of cracks.
- SegNet uses max-pooling indexes obtained during the encoder's pooling steps to implement non-linear upsampling in the decoder.

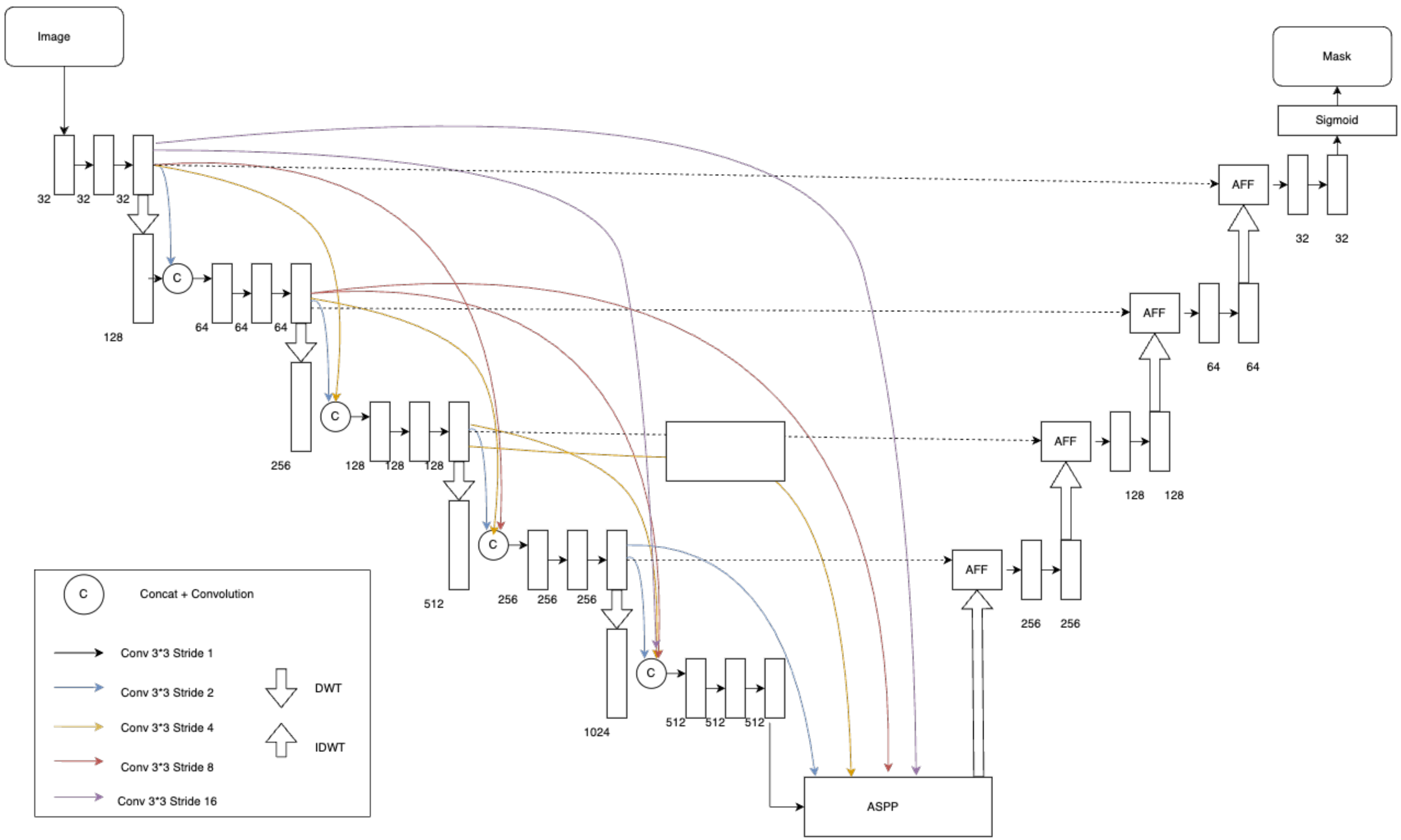
# Self-attention-based models

- Vision transformer.
- Process input images in a patch-based manner, capturing both local and global context to make pixel-wise predictions.
- Needs large amount of data

# Self-attention-based models

- In “A convolutional-transformer network for crack segmentation with boundary awareness ” the author proposed a convolutional-transformer network based on an encoder-decoder architecture with Dilated Residual Block (DRB) which is combined with a lightweight transformer that captures global information to serve as an effective encoder and a Boundary Awareness Module (BAM) was proposed.
- Another study proposes a dual-encoder network fusing transformers and convolutional neural networks (DTrC-Net) to alleviate the influence of irregularly shaped cracks, complex image backgrounds, and to overcome limitations in acquiring global contextual information.

# Architecture Overview



# Architecture Overview - Modules

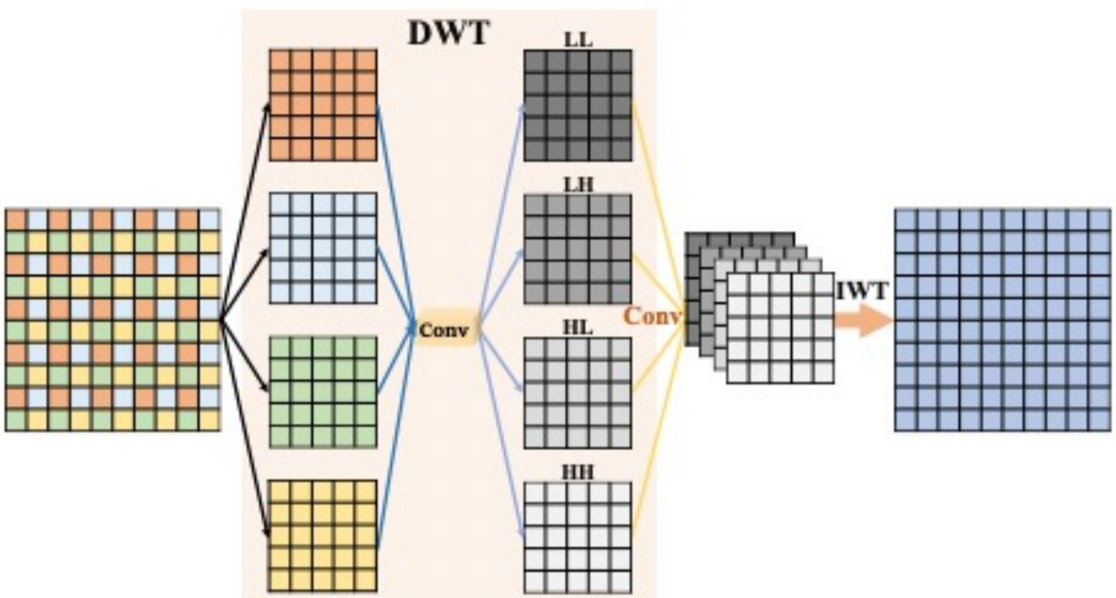
U-net Architecture

- encoder-decoder structure.
- Encoder - captures context and extracts features
- Decoder - reconstructs the spatial resolution

# Architecture Overview - Modules

## Wavelet

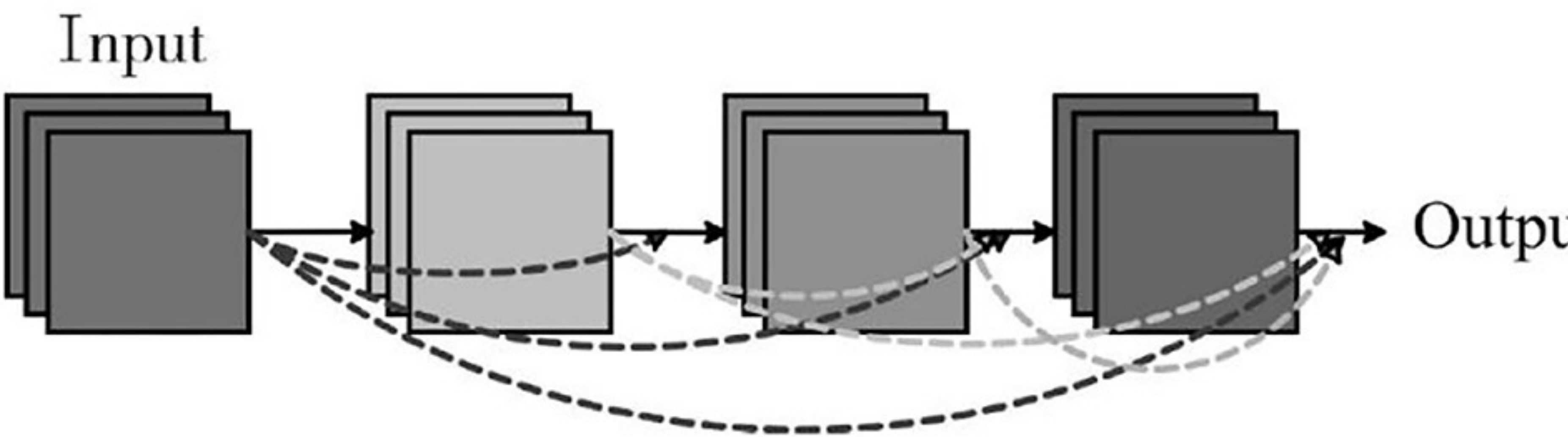
- Pooling- loss of information
- DWT & IDWT



# Architecture Overview - Modules

## Cross level Fusion

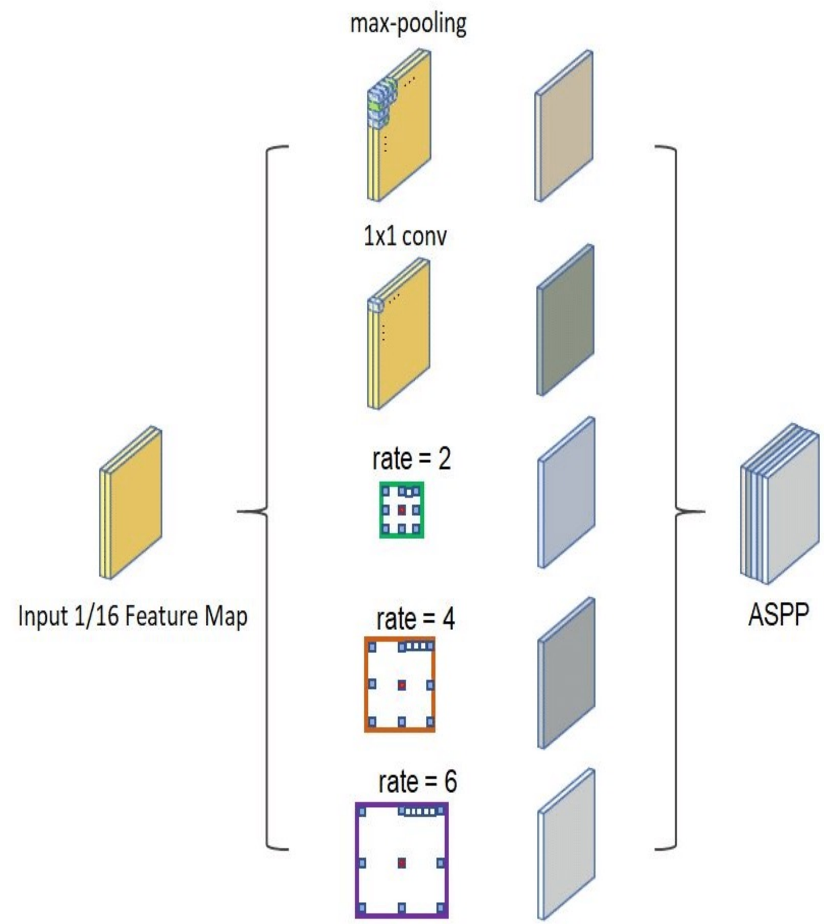
- Dense cross-level connections to fuse the features between the different layers



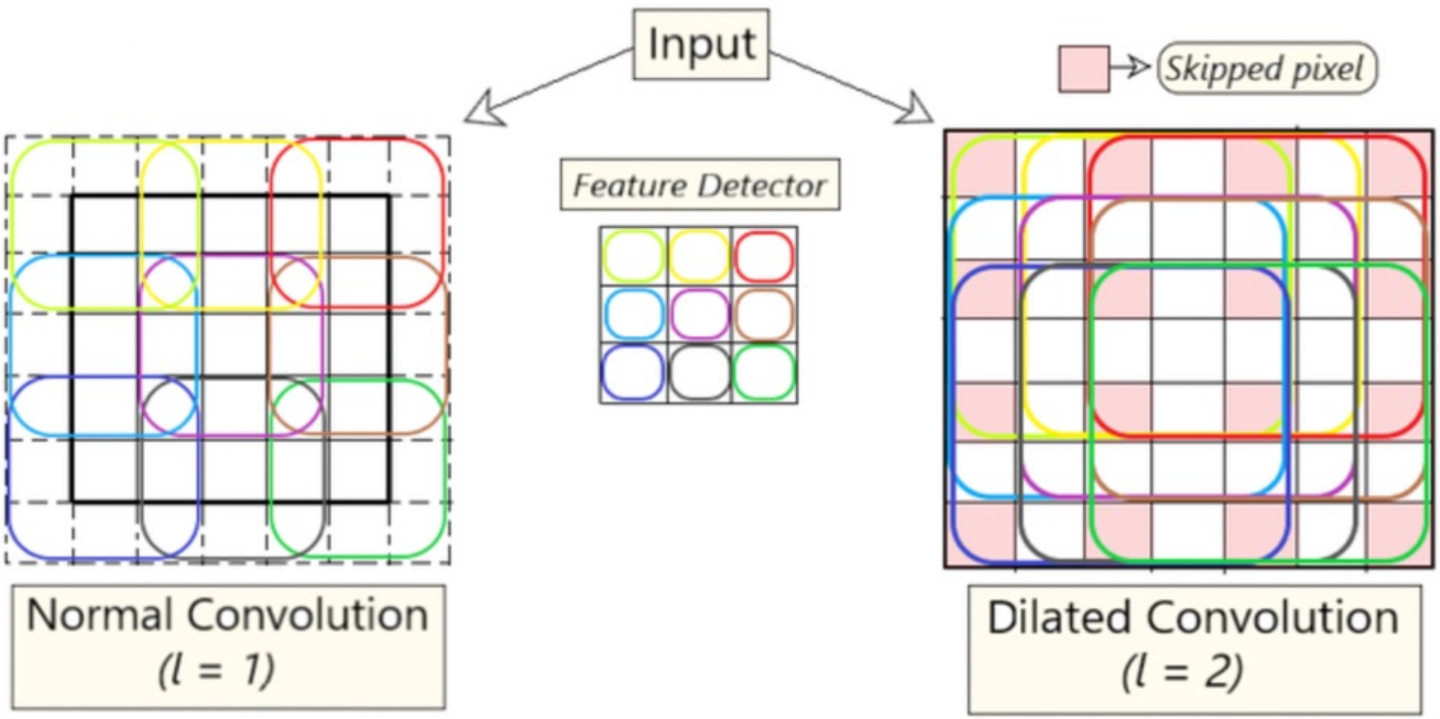
# Architecture Overview - Modules

Atrous spatial pyramid pooling:

- gains the ability to capture multi-scale contextual information efficiently
- Used in concatenation with dense cross level connections.
- Uses Dilated Convolution



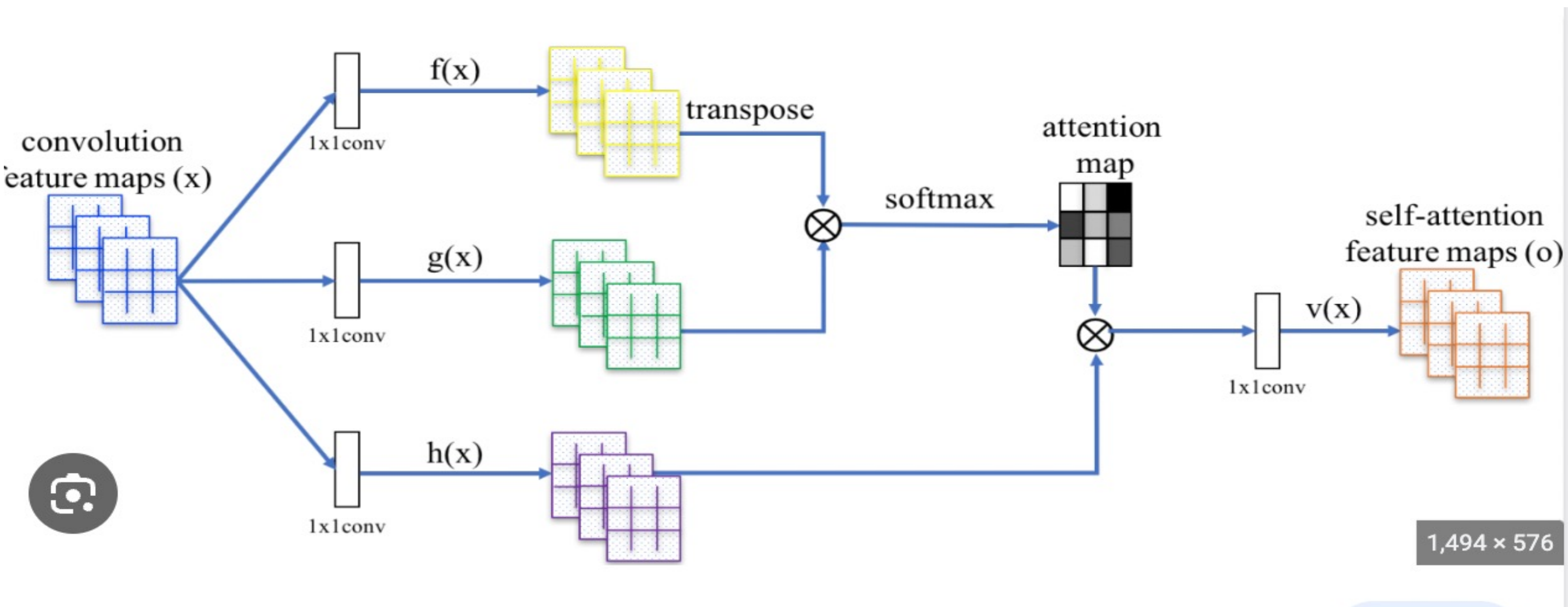
# Architecture Overview - Modules



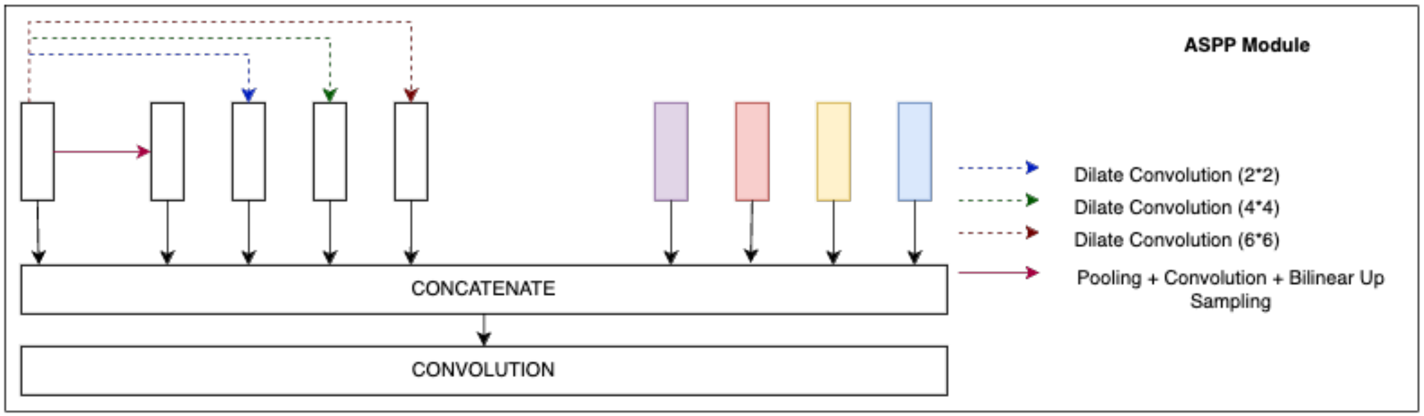
# Architecture Overview - Modules

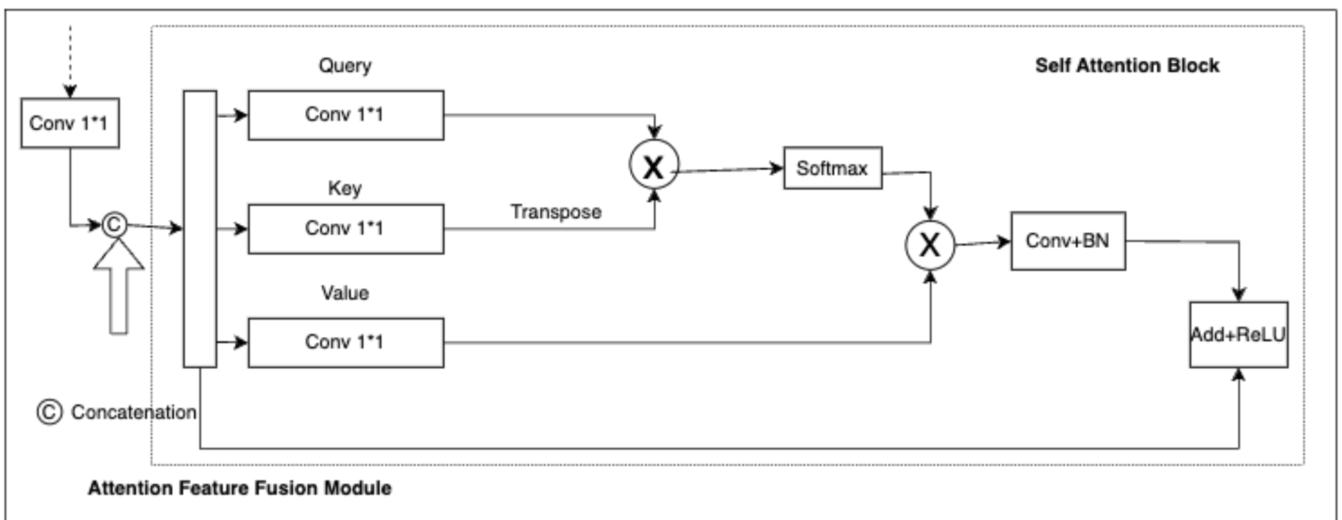
## Attention feature fusion:

- Self-attention: to pay attention to important features



# Architecture Overview



# Loss Function

$$\text{BCE Loss} = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \cdot \log(p_i) + (1-y_i)\cdot \log(1-p_i)\right]$$

where:

- $N$ is the number of samples in the dataset.
- $y_i$ is the ground truth label for the $i$-th sample (either 0 or 1).
- $p_i$ is the predicted probability that the $i$-th sample belongs to class 1.

# Training

- Trained on 10000 images.
- BCE Loss
- 5-fold cross validation
- 30 epoch
- Learning rate `1e-4`
- Batch Size: 8
- Early stopping- patience-5

# Validation Metrics

- Dice Coefficient:

$$Dice = \frac{2 \times |A \cap B|}{|A| + |B|}$$

- IOU:

$$IoU = \frac{|A \cap B|}{|A \cup B|}$$

# Validation Metrics

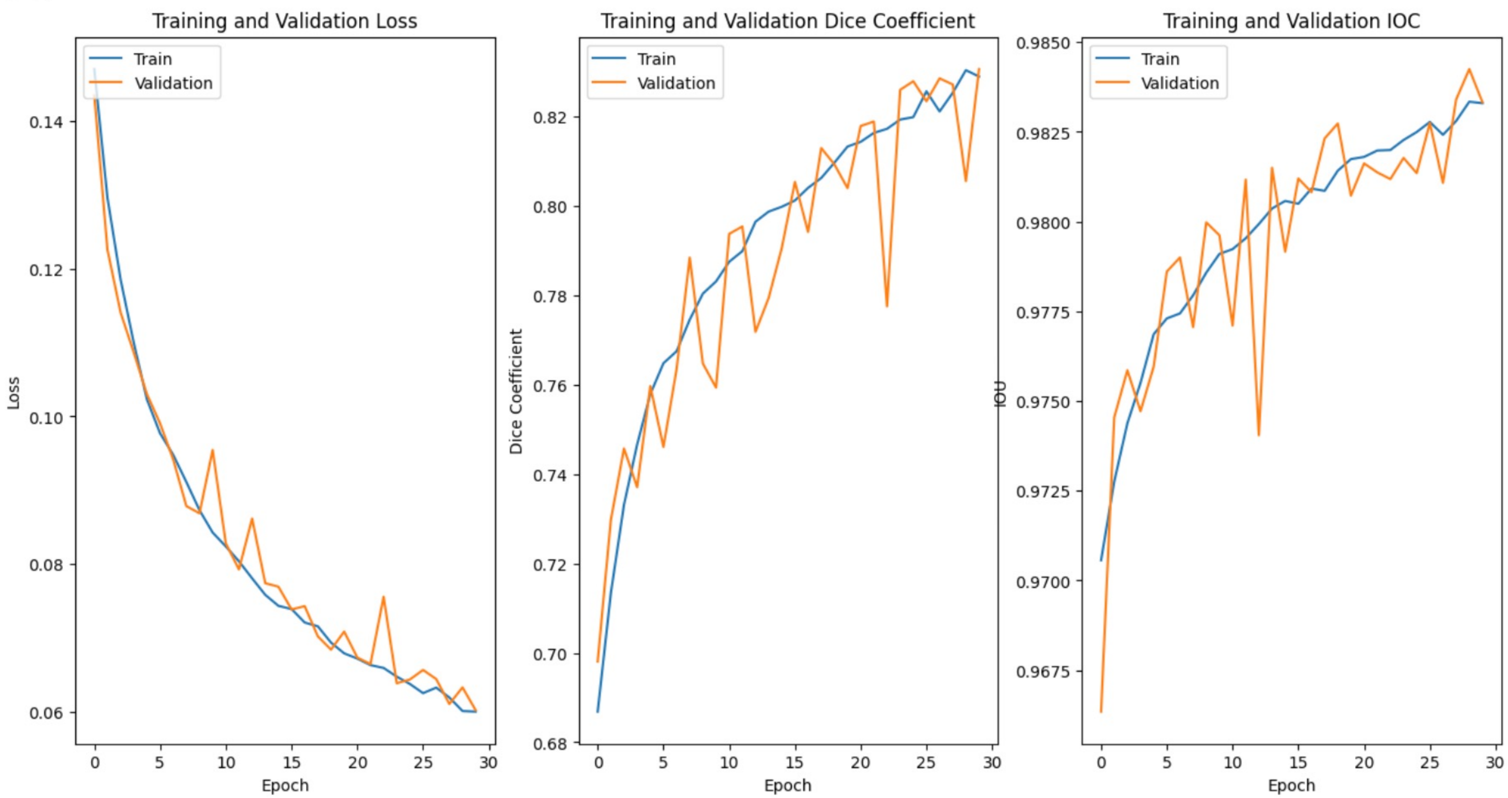
- ROC Curve:

graphical representation of the trade-off between true positive rate (sensitivity) and false positive rate (1 - specificity) for different threshold values.

- AUC:

Area under the curve. Scalar value from 0 to 1

# Results

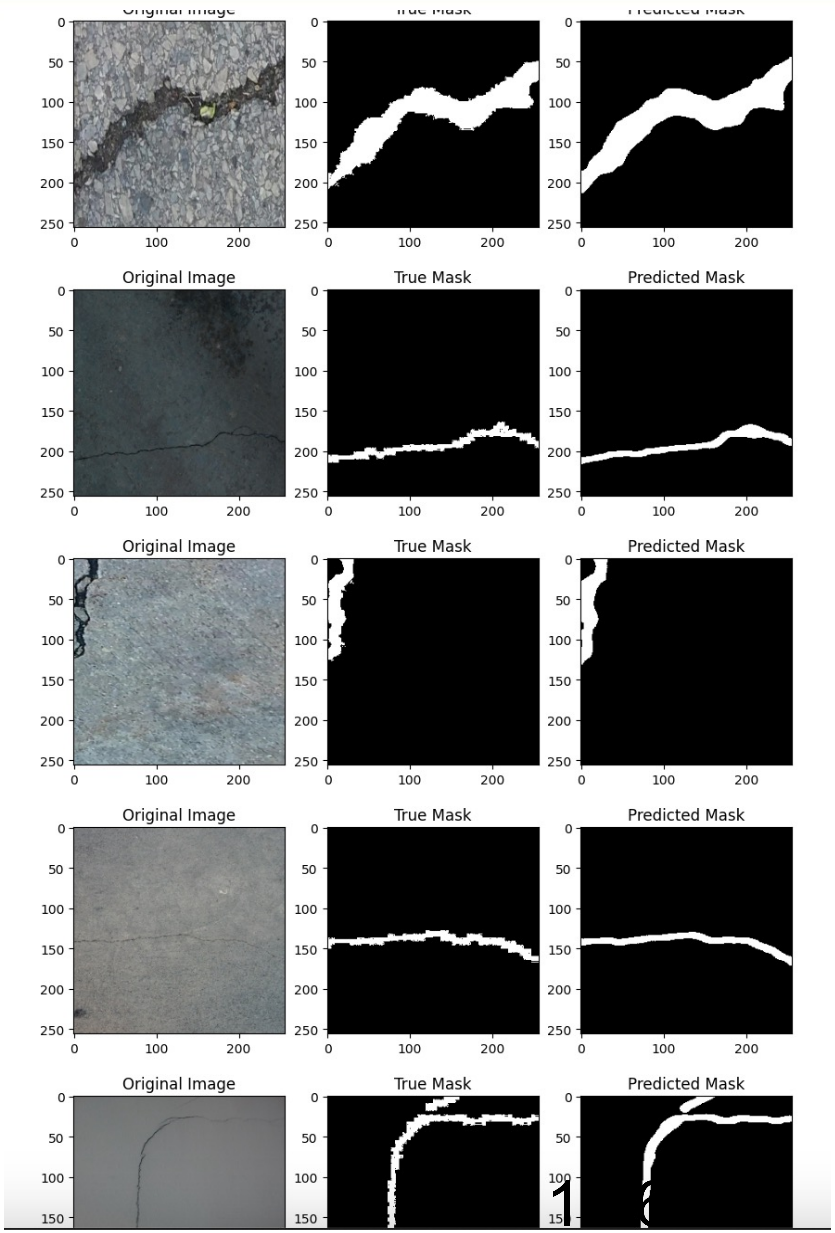

Training and Validation Loss
Train
Validation
Loss
Epoch
Training and Validation Dice Coefficient
Train
Validation
Dice Coefficient
Epoch
Training and Validation IOC
Train
Validation
IOU
Epoch

# Results

- Dice Coefficient on Test Data: 0.77
- Test F1 Score: 0.978
- IOU on Test Data: 0.64
- AUC on Test Data: 0.87

# Results

- Results of experiment on test dataset



# Challenges and Future Work

- Augmentation
- Transfer Learning

# Conclusion

- U-net Model with Dense Cross-level connections and self-attention mechanisms to capture the fine details as well as the context information to segment the road cracks

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# Thank You

Questions?