Erasmus
School of
Economics

# A Bayesian Convolutional Neural Network Approach

for Image-Based Crack Detection and a Maintenance Application

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# We are living in the Golden Ages of machine learning

## Why?

- **Data availability**
  - Data is the new oil
- **Computing power**
  - Affordable & accesible

## What?

- **Decision Making & Autonomous control**
  - Buy a stock (yes/no)?
  - Will my client default?
  - When will my machine break down?
  - Face-recongition
  - Self—driving cars
  - Chatbots

**Not a question of if but when**

# The practical applicability concerns a trade-off between high accuracy and reliability

## Drawbacks

- **"Black-Box"**
  - Will patient X need surery or not?

- **Uncertainty**
  - Intelligent prediction or random guess?
  - Can be dangerous life-threatening situations

# Can we quantify the uncertainty in image-based crack detection for concrete structures using a Bayesian Convolutional Neural Network?

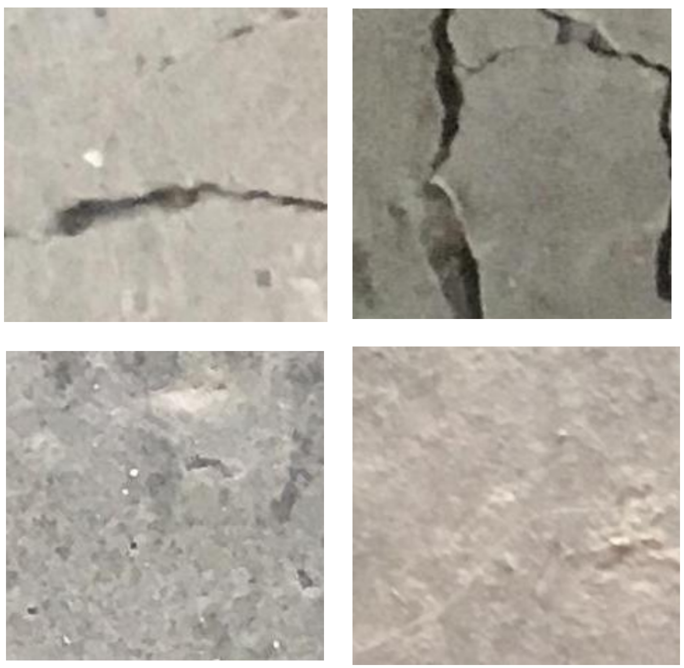
- **Maintenace Application**
  - Cracks & Chemical detoriation
  - System failures
  - Labor-intensive, subjective, dangerous
- **Image-based methods in practice**
  - CQM
    - Railroad inspection with CNNs
    - No measure of uncertainty


**We want a model that knows when they don't know!**

# The Bayesian convolutional neural network aggregates from neural networks and Bayesian learning to obtain a probabilistic framework.

## Data Set

40,000 images of concrete structures



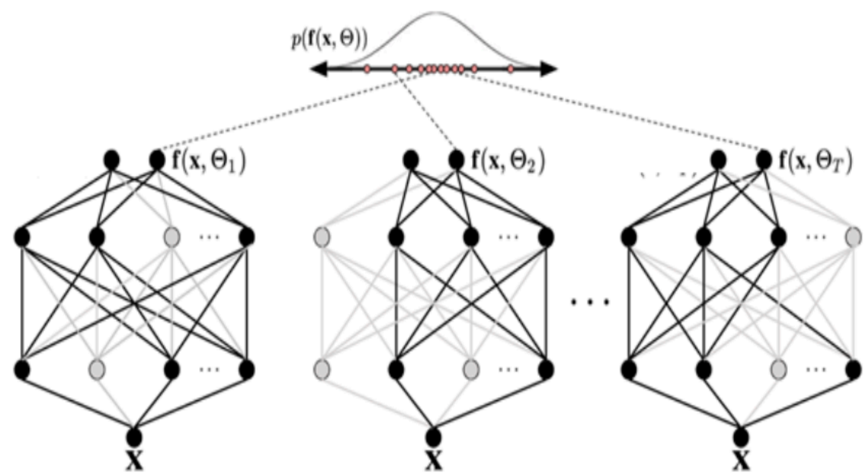
Özgenel, Çağlar Fırat (2019), "Concrete Crack Images for Classification", Mendeley Data, v2
http://dx.doi.org/10.17632/5y9wdsg2zt.2

## Bayesian convolutional Neural Network

*Bayesian learning + neural networks*

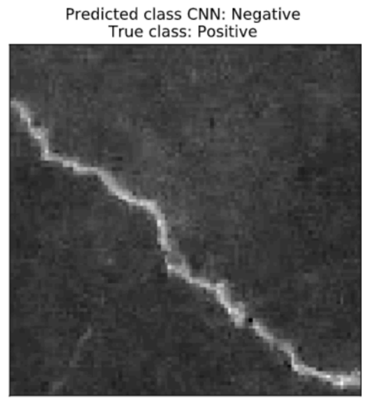
Does the image contains a crack? Yes or No?

## Monte Carlo Dropout

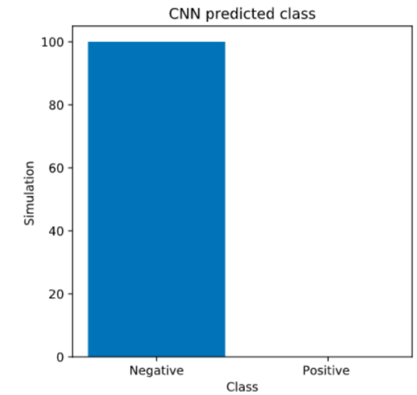


# The Bayesian method is able to measure the uncertainty and reduce the false negatives compared to traditional models

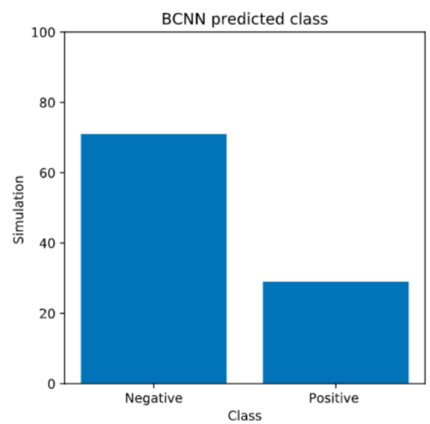
- CNN wrongly predicts no crack with p = 0.76
- BCNN correctly classifies the image in some of the cases.
- The variance is high, the model not sure about the outcome



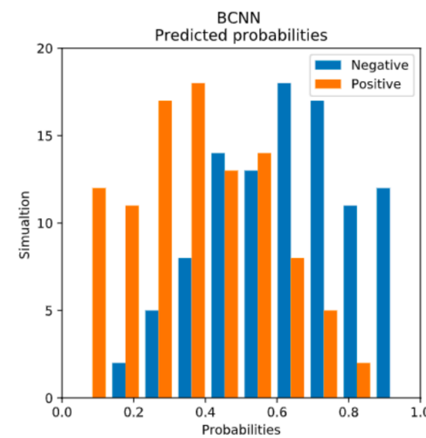

**(a)** False negative prediction




**(b)** Predicted probabilities for 100 simulations




**(c)** Predicted class for 100 simulations




**(d)** Predicted probabilities for 100 simulations

# The Bayesian convolutional neural network can measure uncertainty, and domain experts confirms it's potential

## Recommendations & Limitations

- Advantages over the traditional methods
- Widely applicable for all kinds of anomaly detections
- CQM domain expert confirms it's potential and the importance of model uncertainty
- Questioned by other researchers on its theoretical foundation
- Running time

## Further Research

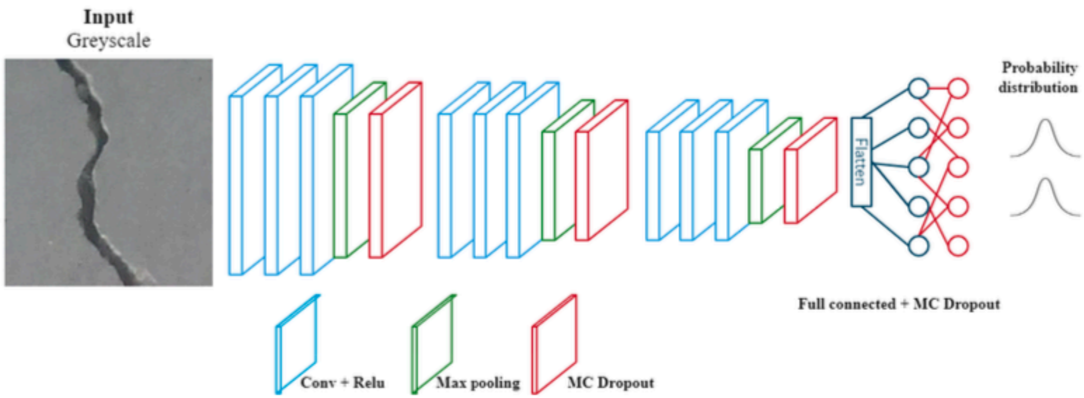
* Research on outlier images
* Human in the loop

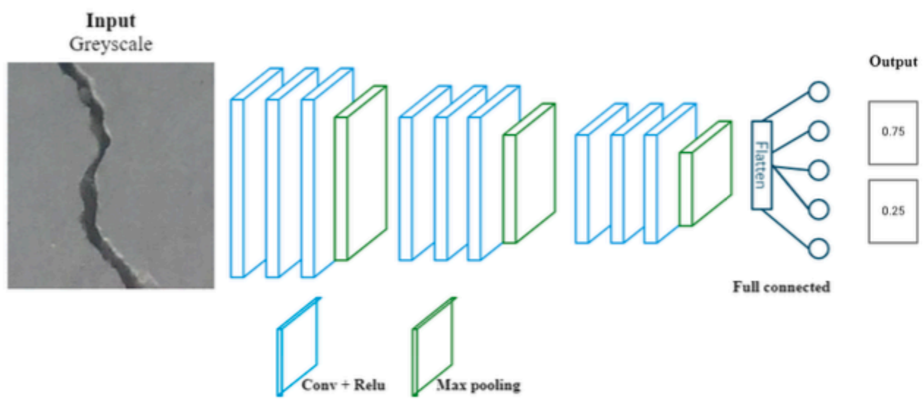
# Thank you for listening!

## Are there any questions?

# APPENDIX I

Model arichtectures
**Github**: https://github.com/Tasiabueno/Bayesian-Convolutional-Neural-Network-Crack-Detection

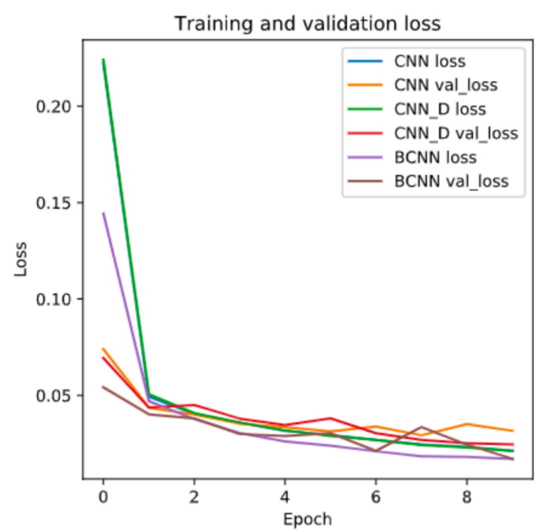


# APPENDIX II

Model preformance

| | **Accuracy** | | | **Loss** | | |
|---|---|---|---|---|---|---|
| Model | Train | Val | Test | Train | Val | Test |
| CNN | 0.993 | 0.992 | 0.993 | 0.021 | 0.032 | 0.026 |
| CNN_D | 0.993 | 0.992 | 0.993 | 0.021 | 0.025 | 0.025 |
| BCNN | 0.995 | 0.994 | 0.994 | 0.017 | 0.171 | 0.018 |




| **BCNN** | | Predicted ($p > 0.50$) | | | Predicted ($p > 0.70$) | | |
|---|---|---|---|---|---|---|---|
| | | Negative | Positive | All | Negative | Positive | All |
| True | Negative | 2821 | **179** | 3000 | 2821 | **179** | 3000 |
| | Positive | **0** | 3000 | 3000 | **0** | 3000 | 3000 |
| | All | 2654 | 3346 | 6000 | 2654 | 3346 | 6000 |

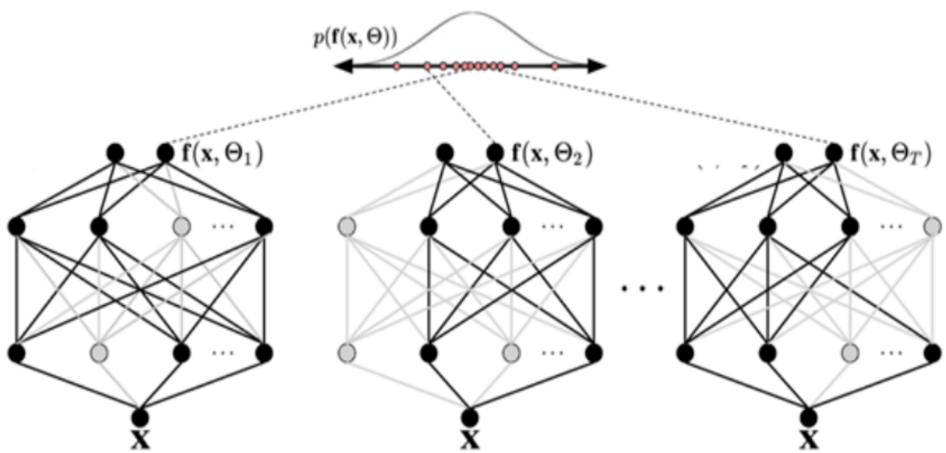
| **CNN** | | Predicted ($p > 0.50$) | | | Predicted ($p > 0.70$) | | |
|---|---|---|---|---|---|---|---|
| | | Negative | Positive | All | Negative | Positive | All |
| True | Negative | 2980 | **20** | 3000 | 2973 | **27** | 3000 |
| | Positive | **21** | 2979 | 3000 | **12** | 2988 | 3000 |
| | All | 3001 | 2999 | 6000 | 2985 | 3015 | 6000 |

| **CNN_D** | | Predicted ($p > 0.50$) | | | Predicted ($p > 0.70$) | | |
|---|---|---|---|---|---|---|---|
| | | Negative | Positive | All | Negative | Positive | All |
| True | Negative | 2976 | **24** | 3000 | 2960 | **40** | 3000 |
| | Positive | **15** | 2985 | 3000 | **11** | 2989 | 3000 |
| | All | 2991 | 3009 | 6000 | 2971 | 3029 | 6000 |

# APPENDIX III

Monte Carlo Dropout

$$P(\hat{y}_i = k|\boldsymbol{x}_i, \boldsymbol{\beta}) \approx \int P(\hat{y}_i = k|\boldsymbol{x}_i, \boldsymbol{\beta}) q^*_{\boldsymbol{\theta}}(\boldsymbol{\beta}) d\boldsymbol{\beta},$$
$$\approx \frac{1}{T}\sum_{t=1}^{T} P(\hat{y}_i = k|\boldsymbol{x}_i, \hat{\boldsymbol{\beta}}_t),$$



# APPENDIX IV

False negative – False postivie trade-off
Variance as uncertainty measure


Questions other researchers?

- Posterior distirubition does not concetrate when more data become availible - Osband

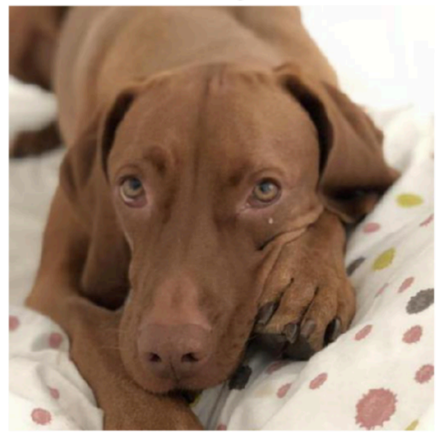
https://arxiv.org/pdf/1711.02989.pdf

# APPENDIX V

Softmax probabilites are not a measure of uncertainty

Prediction: dog
Probability: 0.98

Prediction: dog
Probability: 0.95



https://arxiv.org/pdf/1812.05720.pdf

Nguyen & O'Connor, 2015; Yu et al., 2010; Provost et al., 1998; Nguyen et al., 2015