DETECTING BUILDING DEFECTS

USING COMPUTER VISION AND HARDWARE SUPPORT TO IDENTIFY AND DETECT EXTERNAL DAMAGES TO BUILDINGS

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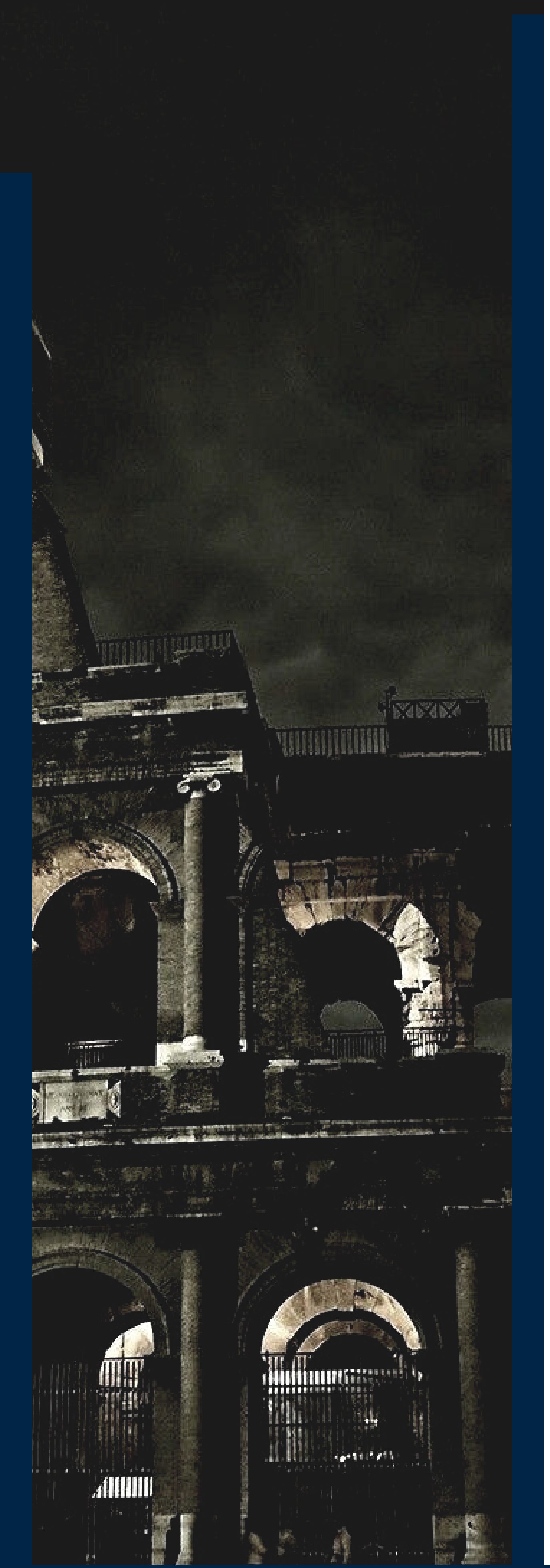
AGENDA

Introduction
Literature Review
Design and Implementation
Future Enhancements
References

INTRODUCTION

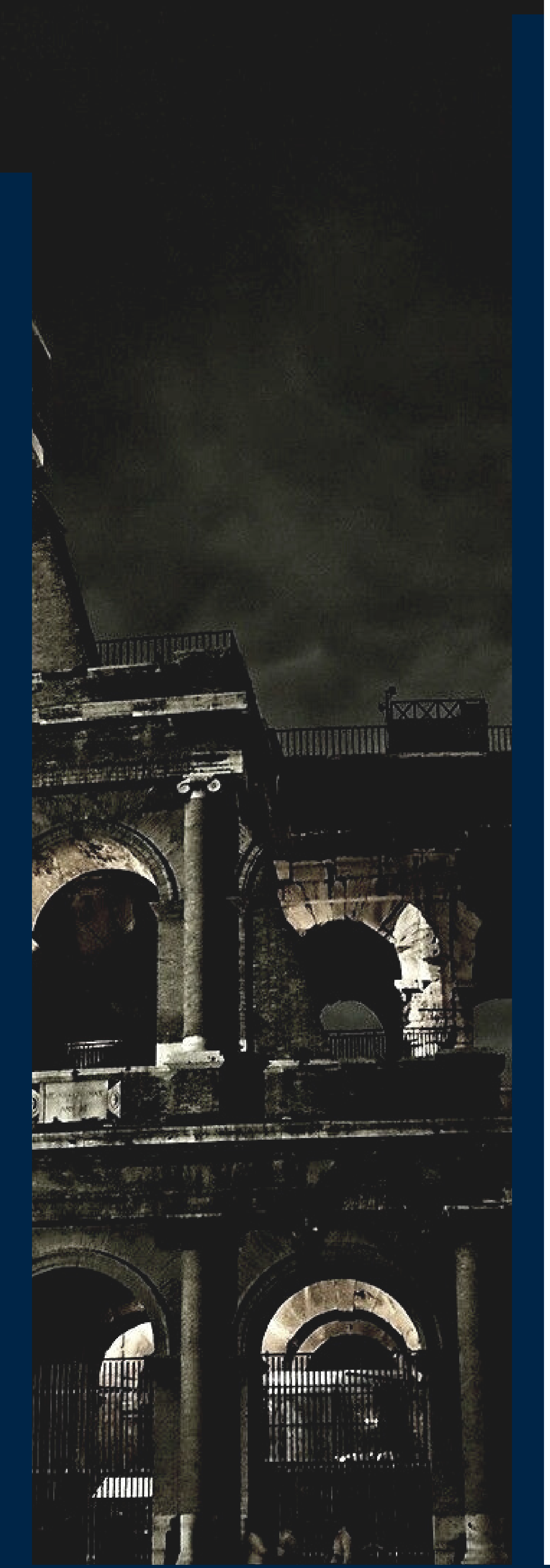


MOTIVATION

TENANTS
Will Need a Safe Home

CONSTRUCTION COMPANIES
Will Need to Establish Credibility

GOVERNMENT AGENCIES
Will Need to Evaluate



RELEVANCE OF OUR WORK

DETECTING DEFECTS

Detect defects in buildings

IDENTIFY INTENSITY

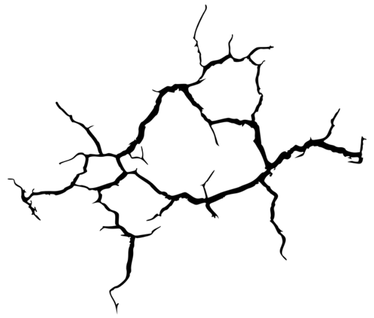
Identify the intensity of the detected defects

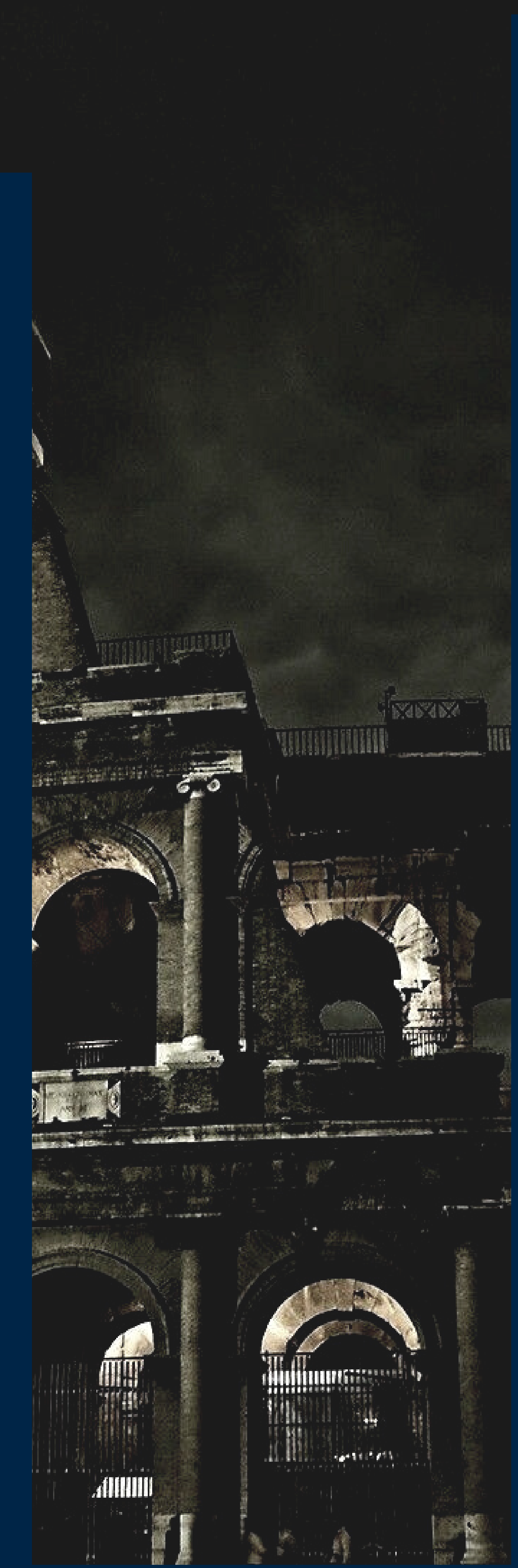
WORK IN REAL-TIME

Real-time working will help stakeholders have better results

PROBLEM STATEMENT

To Build a Model that will Detect external damage to a building and Assess the intensity of the defect and Inform stakeholders about the conditions; thus Reducing the need of Manual Inspection.





DATA COLLECTION

- DATA WAS SCARCE
- TRIED CROWD-SOURCING DATA AT COLLEGE : RECEIVED NO IMAGES
- COLLECTED OUR OWN DATA

40,000
CNN Dataset

1000
Datatturks Dataset

<100
Google Images

<30 But segmented to 4k
Handheld Device Data

LITERATURE REVIEW

LITERATURE SURVEY SUMMARY

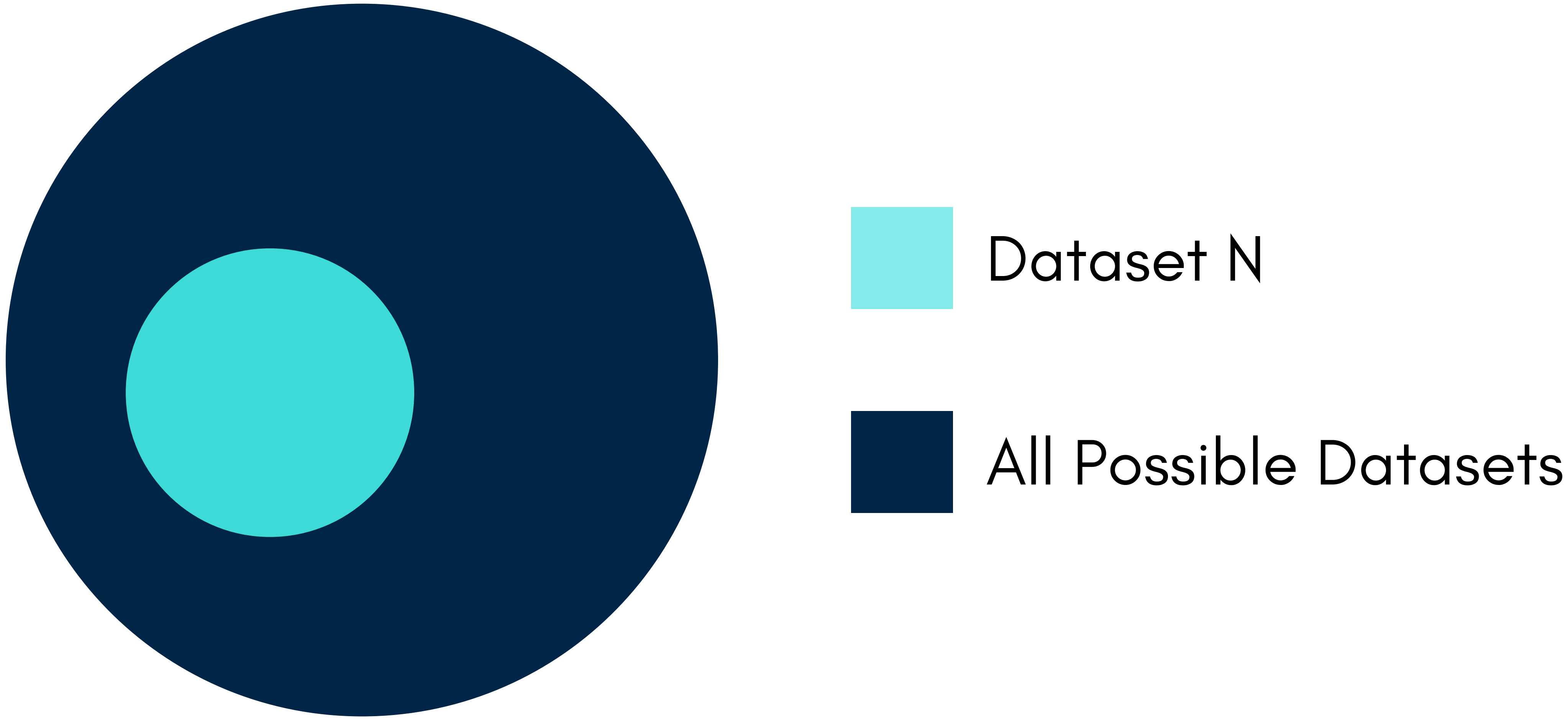
Author and Year	Name	Objective	Approach
Mohan et. al (2016) Alexandria Engg. Journal	Crack detection using image processing : A critical review and analysis	Review	Analysing methods to detect cracks using IP
Fujita et. al (2017) Int. Conf. on Machine Vision Applications	Damage detection from aerial images via CNN	Building Damage Detection	Using CNN to detect if a building is washed out or not
Li et. al (2010) Int. Journal of Remote Sensing	Urban building detection from very high resolution imagery using OCSVM and spatial features	Building Damage Detection	Detecting environmental damage to aerial building images

LITERATURE SURVEY SUMMARY

Author and Year	Name	Objective	Approach
Yeon Lee et. al (2007)	A technique based on IP for measuring cracks in the surface of concrete structures	Measuring Cracks	Analysing methods to detect cracks using IP
Hoang (2018) Hindawi Computational Intelligence and Neruscience	Image Processing based recognition of wall defects using ML and steerable filters	Detect and measure cracks	Using SVM with steerable filters to classify types of cracks

WHAT DO THESE WORKS LACK IN ?

- These are only concerned with "Cracks" as potential defect
- All datasets they have used are specific and the ability of their work to deal with any kind of data is not explained



DESIGN AND IMPLEMENTATION

THE 3 TYPES OF DEFECTS

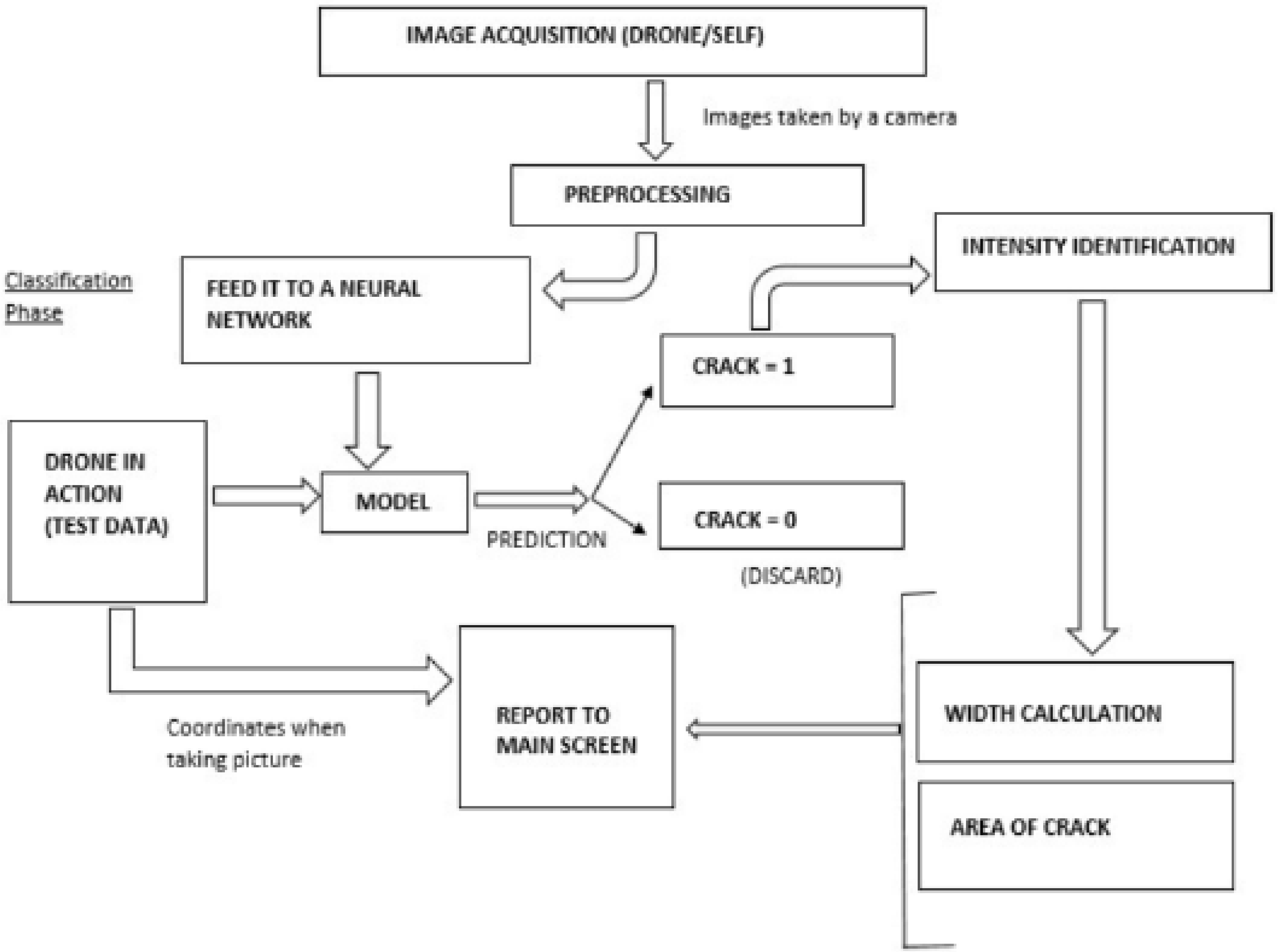
Name of Phase	Crack Detection	ROD Detection	RODP Detection
Availability of Data	Available	Scarce	Scarce
Approach Used	1. DIP 2. Deep Learning	DIP	DIP
Performance	High Accuracy	Rudimentary	Rudimentary
Limitations	1. Shadow 2. Excessive Noise (Prevalent in unpainted, concrete walls) 3. Does not work for Brick Walls	1. Data Scarcity	1. Data Scarcity

Table 1

CRACK DETECTION

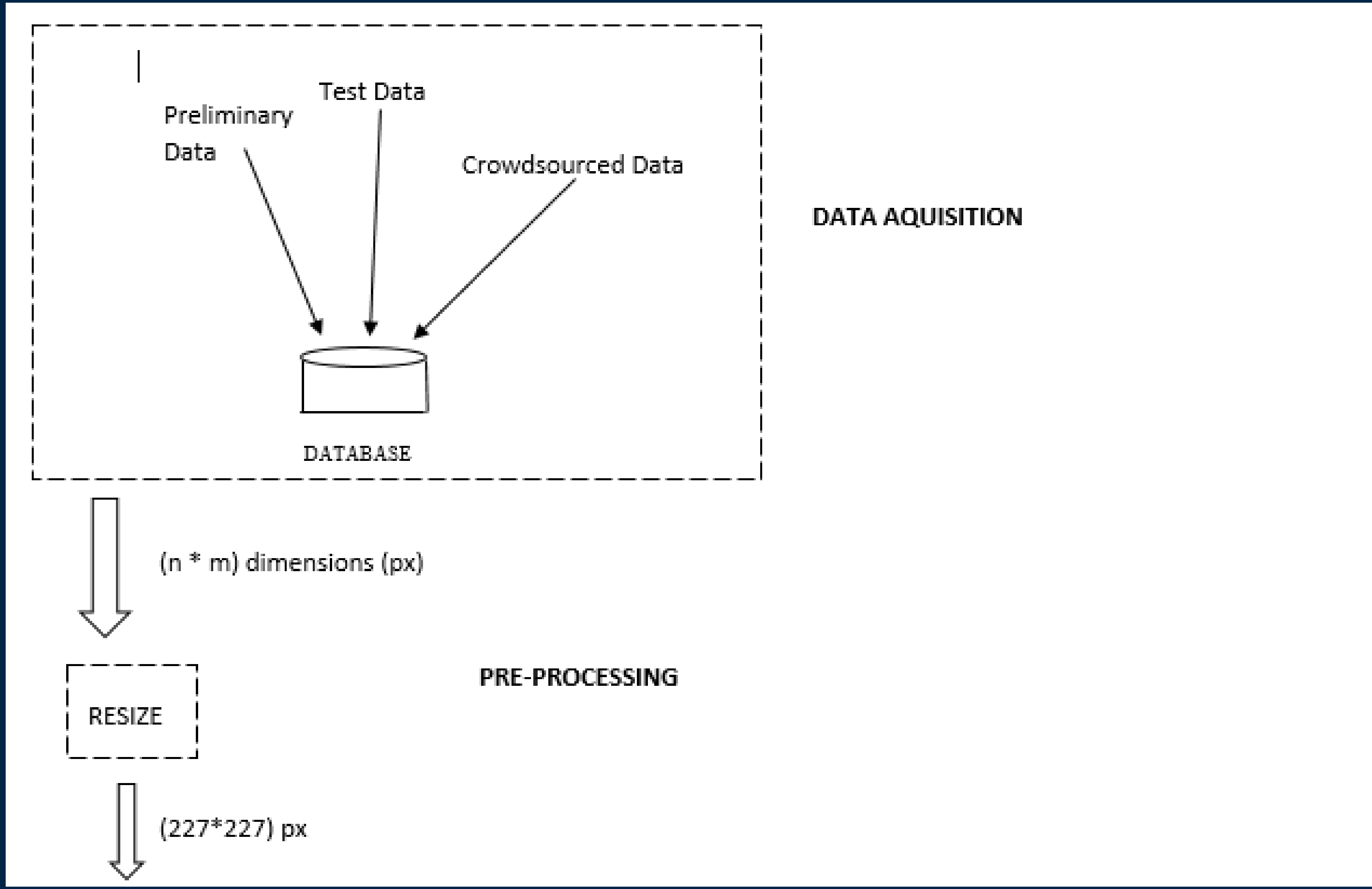
CLASSIFICATION OF CRACKS IN IMAGES

INITIAL PROPOSED ARCHITECTURE

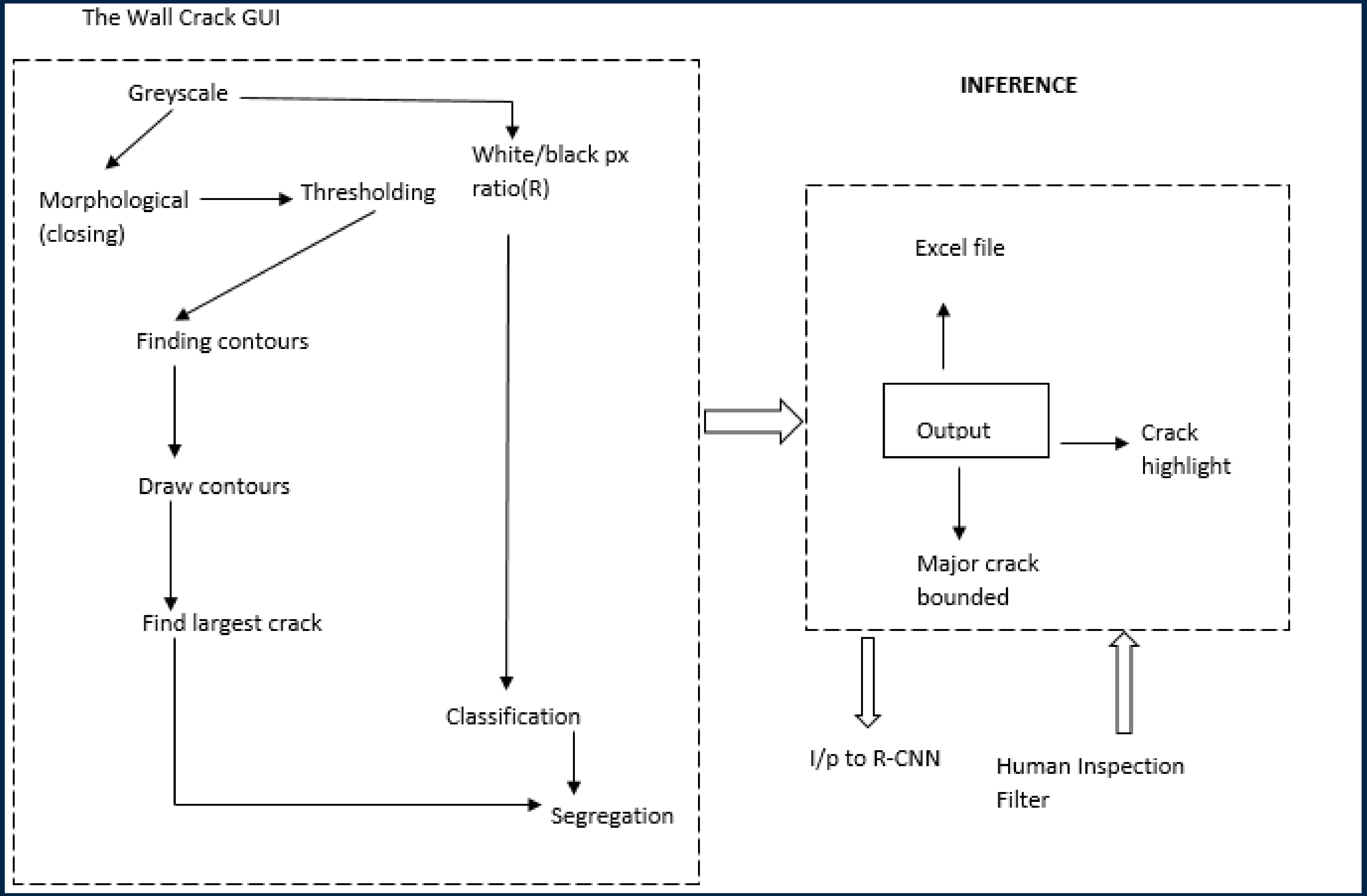


PURE DIP-BASED EMPIRICAL APPROACH

BLOCK DIAGRAM



BLOCK DIAGRAM



HOW DOES THE OUTPUT FILE LOOK ?

	Image Name	Crack Area	White/Black Pixel Ratio	Class
0	00001.jpg	3694.5	0.5467206964	No Crack
1	00002.jpg	952.5	0.1466687436	Crack
2	00003.jpg	2144.5	0.5967586998	No Crack
3	00004.jpg	3818.5	0.4568149049	No Crack
4	00005.jpg	10253	0.7255709597	No Crack
5	00006.jpg	3289.5	0.6270603094	No Crack
6	00007.jpg	1224	0.2984830158	Crack
7	00008.jpg	4523.5	0.6422538802	No Crack
8	00009.jpg	934	0.2573262084	Crack
9	00010.jpg	3677.5	0.409976468	No Crack
10	00011.jpg	4526	0.6044151073	No Crack

HOW ARE WE MAKING SUCH A BOLD CLASSIFICATION ?

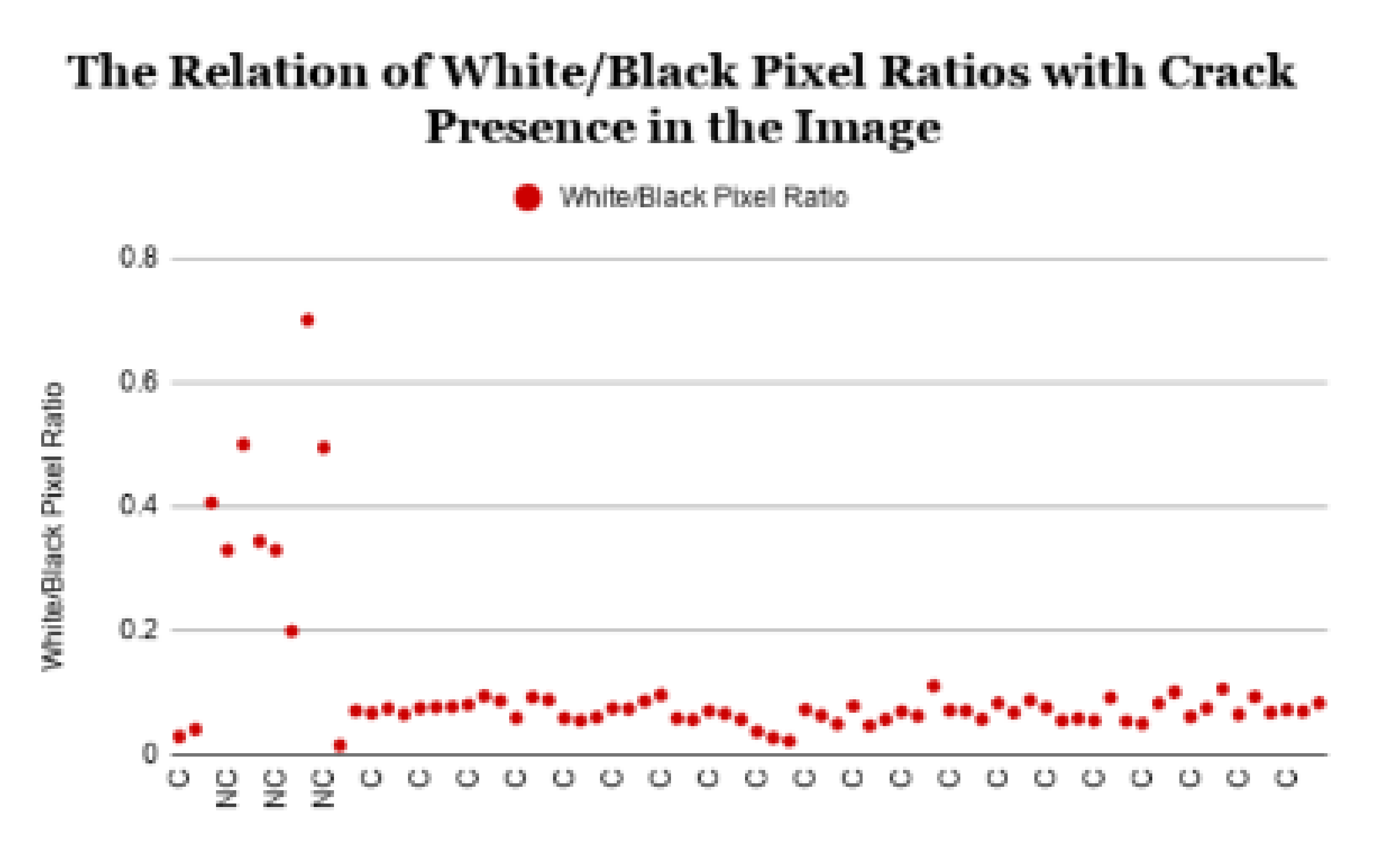
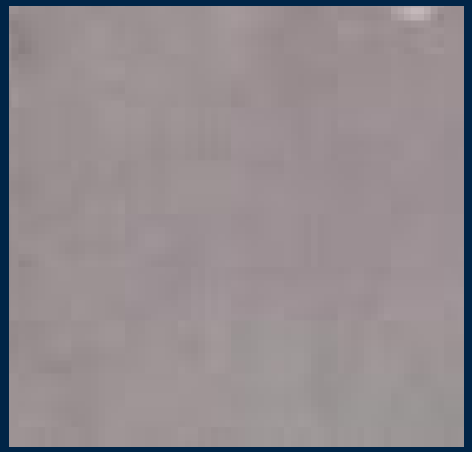


Fig 5.4 (All images not depicted in X-axis)



LOW THRESH

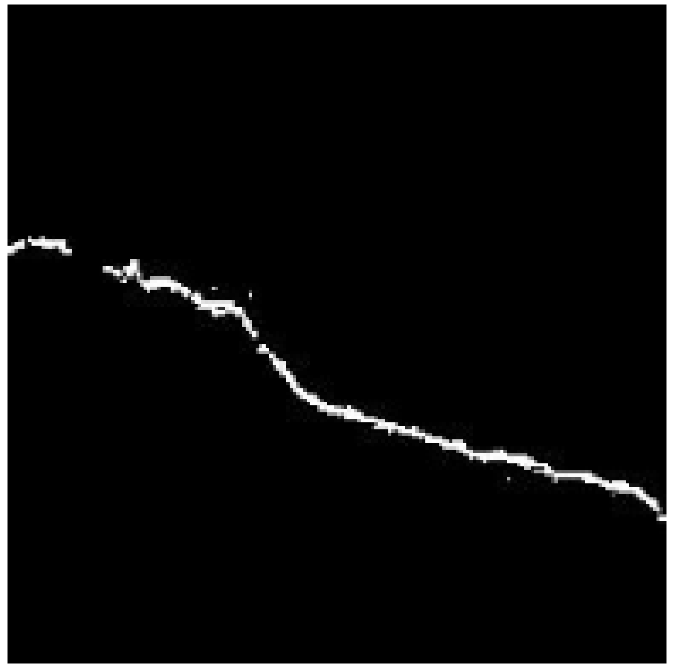
HIGH THRESH

HOW DOES IT PERFORM ?

Dataset	Crack Images	No Crack Images	Accuracy	False Negatives	False Positives
CNN Dataset	500	500	90.2%	1.79%	17.8%
Dataturks Dataset	63	9	97.22%	0%	22.2%
Google Images	27	5	100%	0%	0%

Table 2 (With Otsu Threshold)

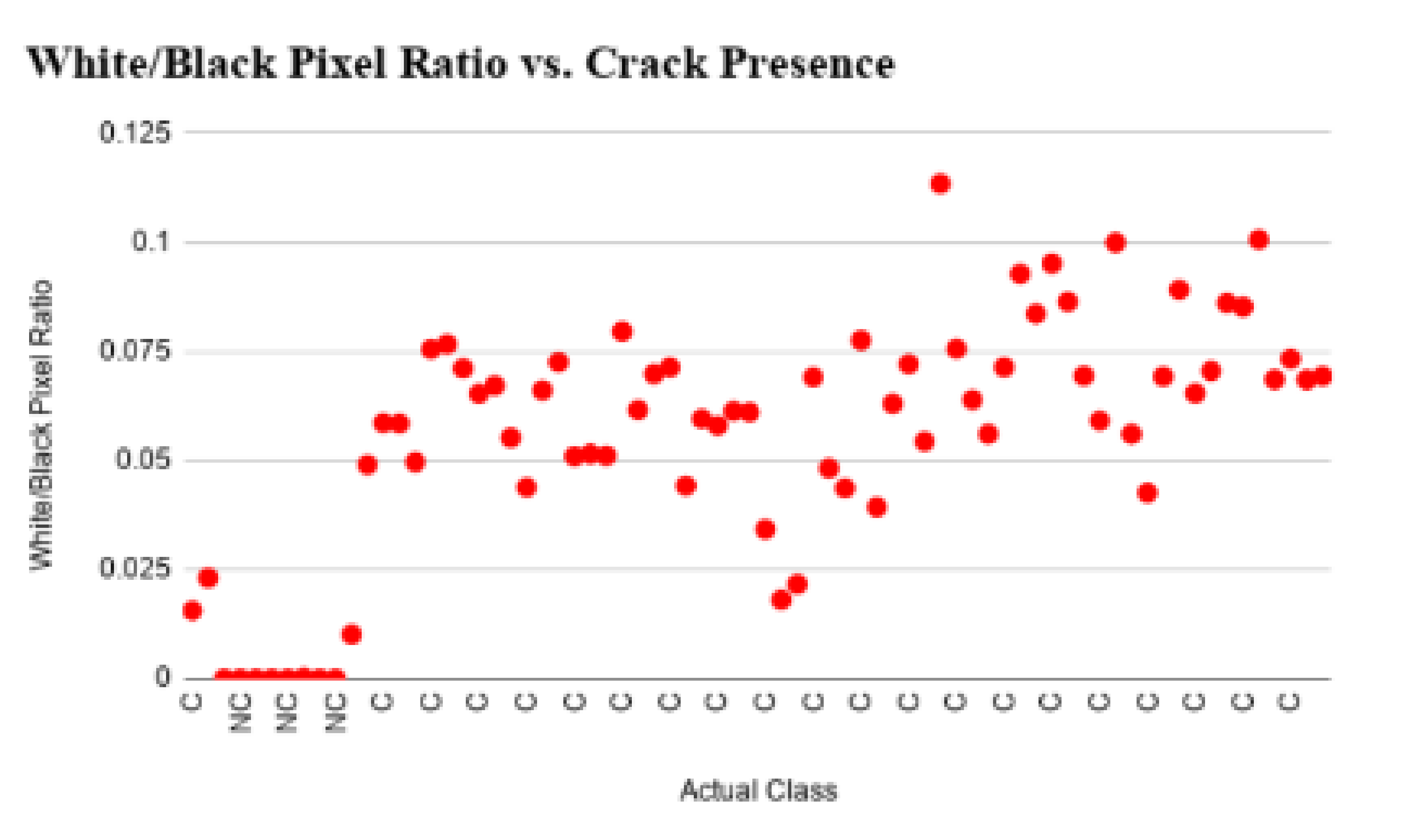
DIFFERENT THRESHOLDING TECHNIQUE ?



OTSU'S METHOD HAS ITS OWN DRAWBACKS

"ADAPT" TO THE SITUATION

USING ADAPTIVE THRESHOLDING



Dataset	Crack Images	No Crack Images	Accuracy	False Negatives	False Positives
CNN Dataset	500	500	86.9%	0%	26.2%
Dataturks Dataset	63	9	98.41%	1.59%	11%
Google Images	27	5	100%	0%	0%

Table 3 (With Adaptive threshold)

PROS AND CONS - PURE DIP APPROACH

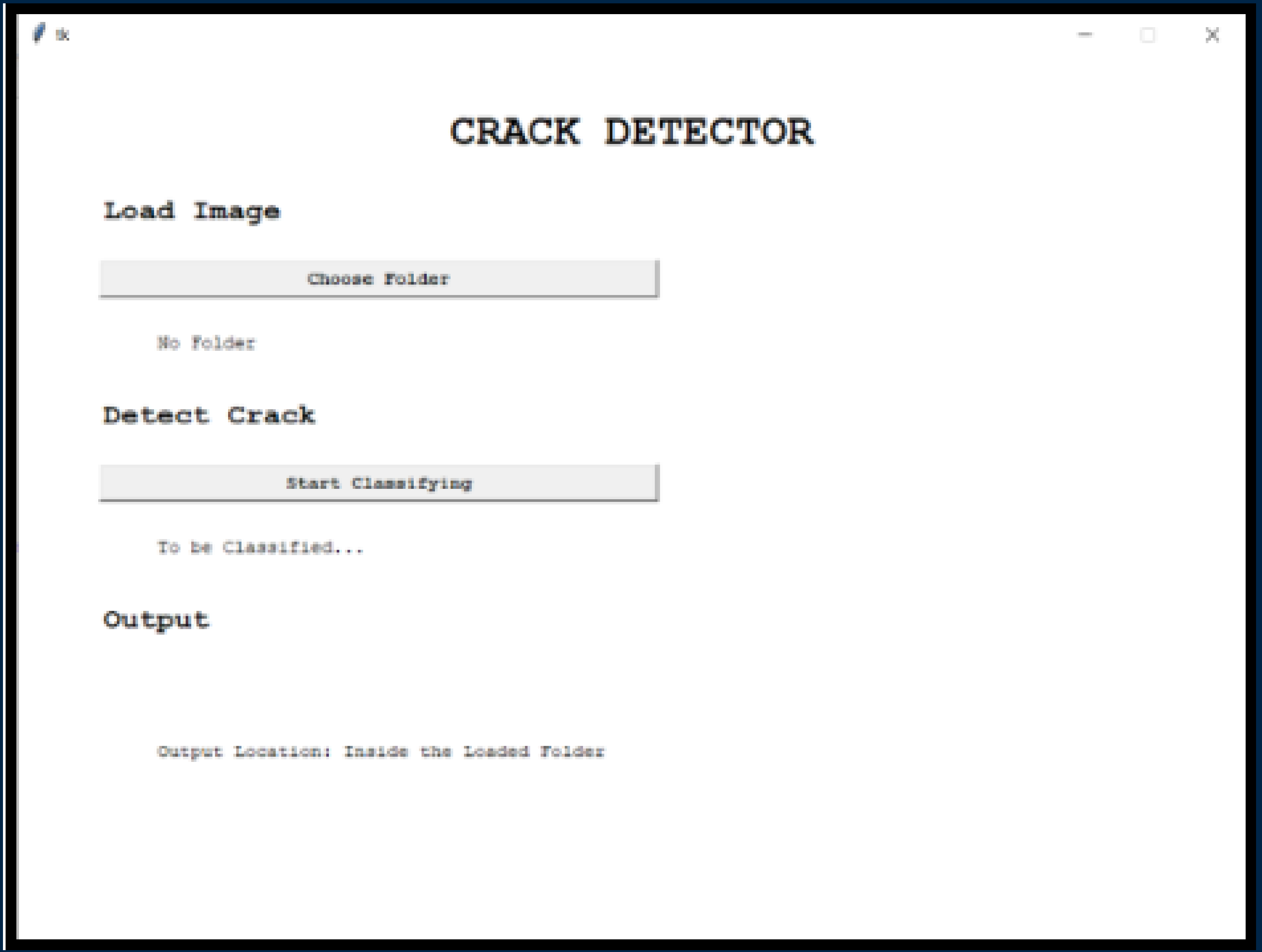
PROS

- No need for Model Training
- Reasonable Accuracy without complexity
- Faster (Around 0.2 seconds per image)

CONS

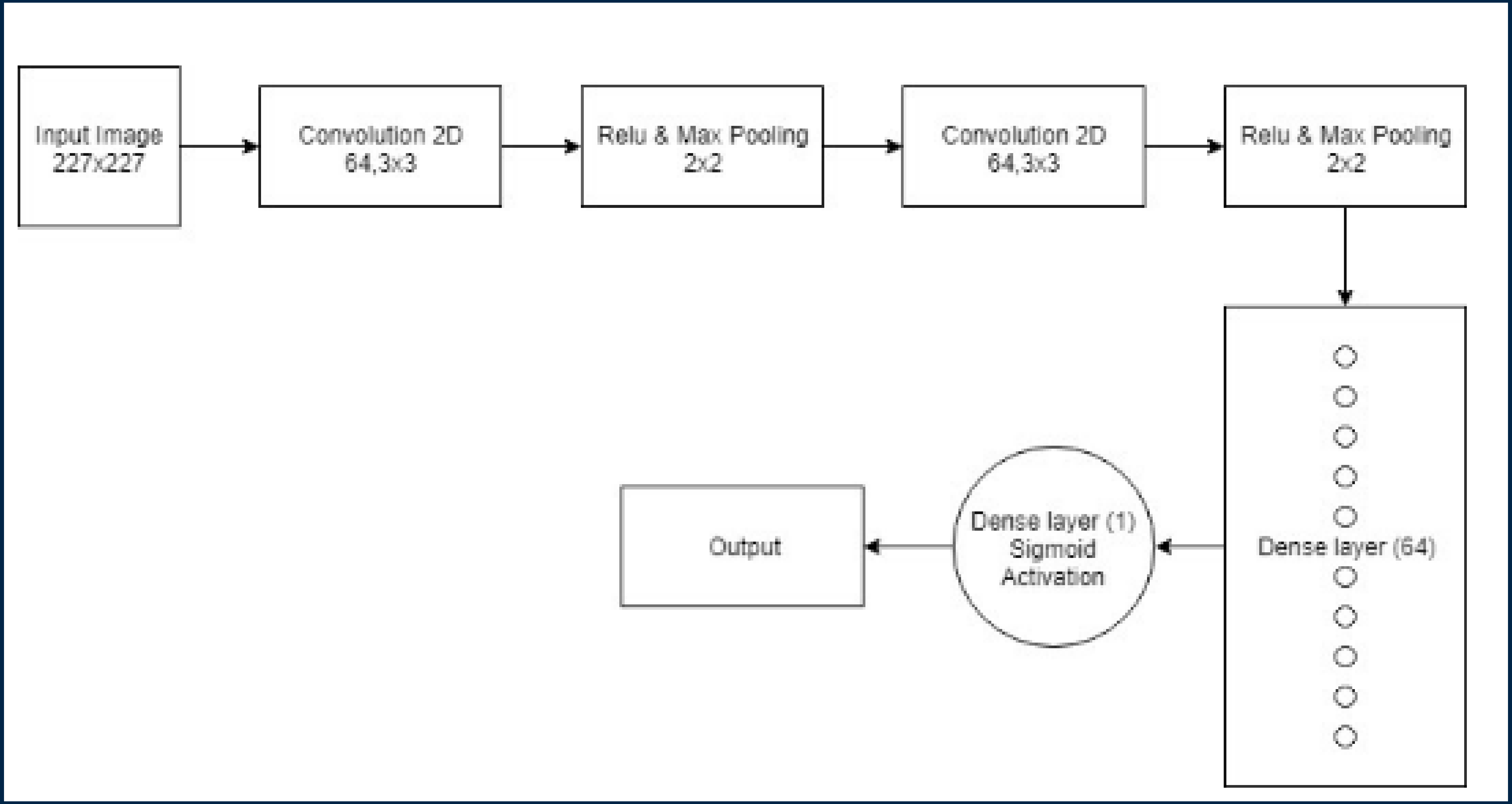
- Threshold method - Very Skeptical Approach
- Not as high an accuracy as CNN
- Can't work for brick walls
- Can't work for noise like doors, hinges, wires etc.

SCREENSHOTS OF THE GUI DEMO



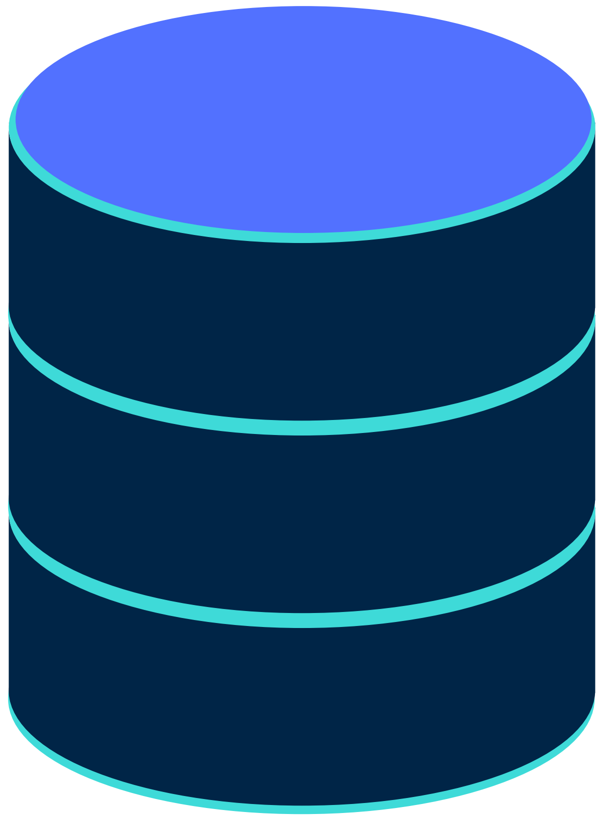
DEEP LEARNING-BASED APPROACH

CNN ARCHITECTURE



CNN TRAINING DATA SPECIFICS

- Origin : CNN Dataset
- Number of Images : 10,000
- Dimension of Images : 227 x 227 pixels
- Number of Epochs : 5
- Validation Split : 10%

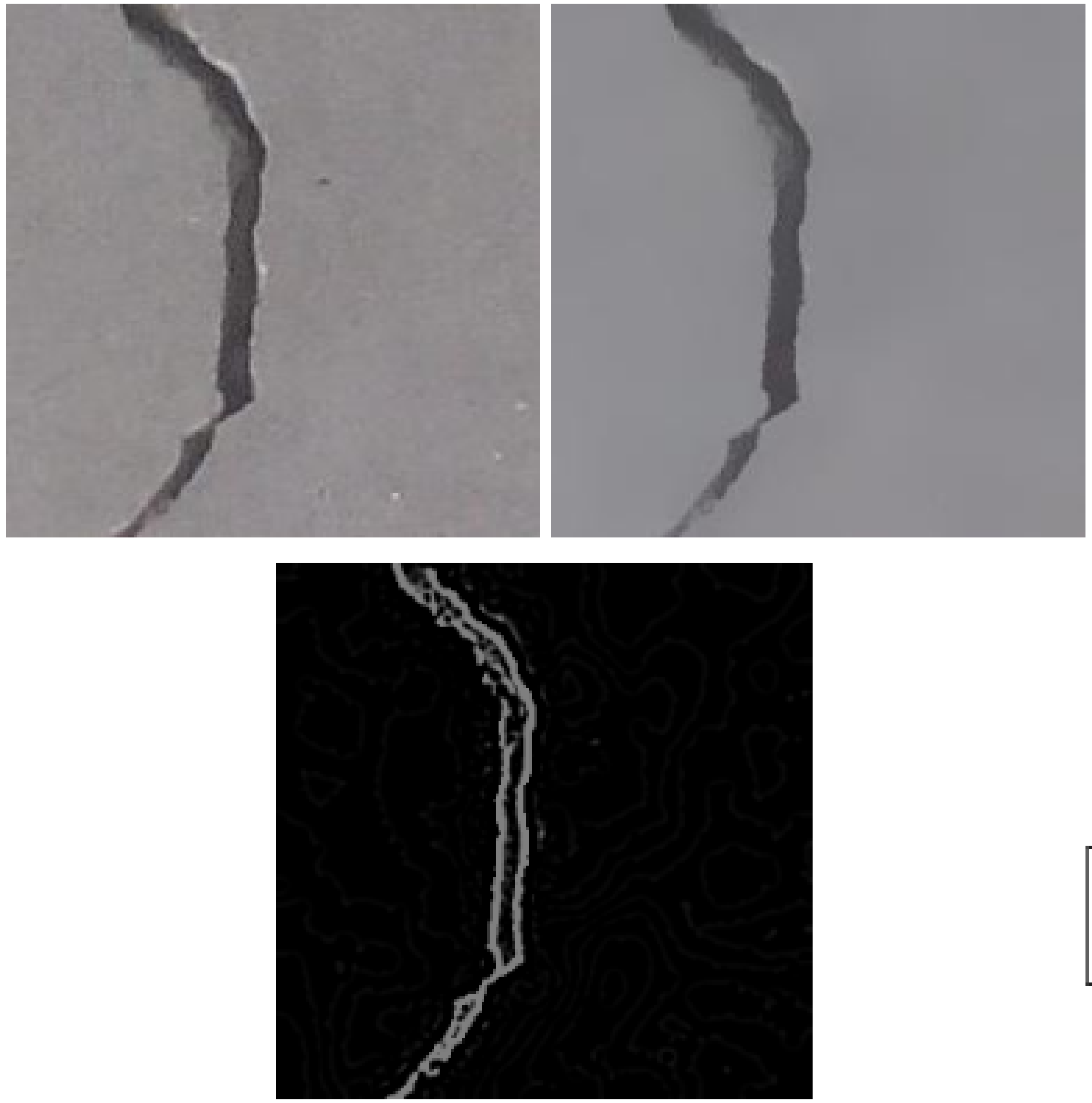


HOW DOES IT PERFORM ?

Dataset	Number of Images	Type of Images	Accuracy
Validation Set	1000	Concrete Walls	99.1%
Google Images	31	Concrete Walls	100%
Handheld Device	197	All kinds	33.5%

Table 4 (Without Preprocessing)

PRE-PROCESSING IMAGES BEFORE CNN



SHARPENING PROVIDES A MORE DISTINCT PATTERN

PREPROCESSING PROCESS

DID IT WORK BETTER ?

Dataset	Number of Images	Type of Images	Accuracy
Validation Set	1000	Concrete Walls	99.89%
Google Images	31	Concrete Walls	60%
Handheld Device	197	All kinds	49%

Table 5 (With Preprocessing)

PROS AND CONS - CNN APPROACH

PROS

- Very high accuracy
- Definite to work well, no skepticism unlike the pure DIP approach

CONS

- Requires large number of training data
- Takes more time
- Does not do well when posed with input that is completely deviant from what it has seen before

THE HANDHELD DEVICE DATA

SPECIFICS OF IMAGE COLLECTION

MODE OF COLLECTION
48 MP CAMERA - REDMI NOTE 8

TIME
5:00 P.M. - 6:00 P.M.

WEATHER
SUNNY

IMAGE DATABASE CREATION

25 IMAGES → 4004 IMAGES → FILTERING OUT BAD IMAGES → FINAL DATABASE

DIP BEATS CNN !

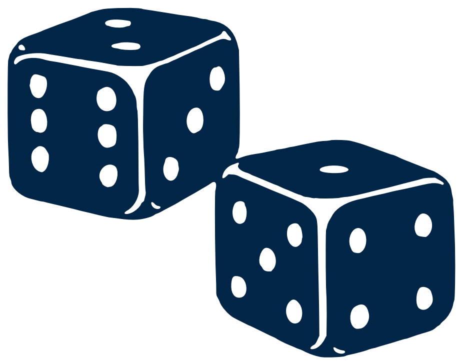
HANDHELD DEVICE DATA

- 118 images (109 cracked, 9 no-crack)
- 227 x 227 pixels
- Sampled from 4k images (segmented from 25 images)
- Each image of 6 KB

Approach	Accuracy
CNN - Without preprocessing	33.5%
CNN - With preprocessing	49%
DIP-based - Otsu	93.22%
DIP-based - Adaptive	85.59%

Table 6 (DIP beats CNN)

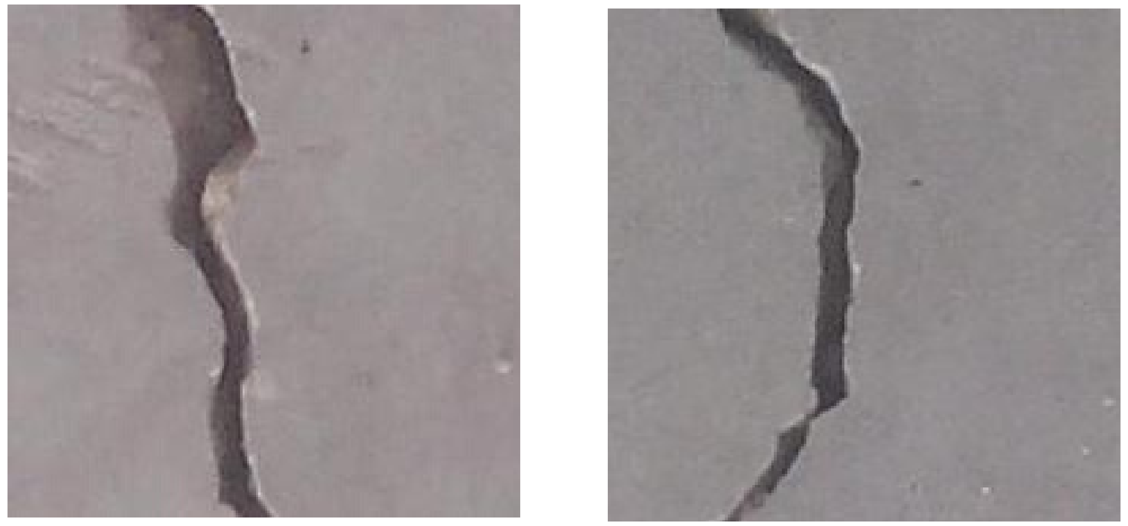
DIP BEATS CNN !



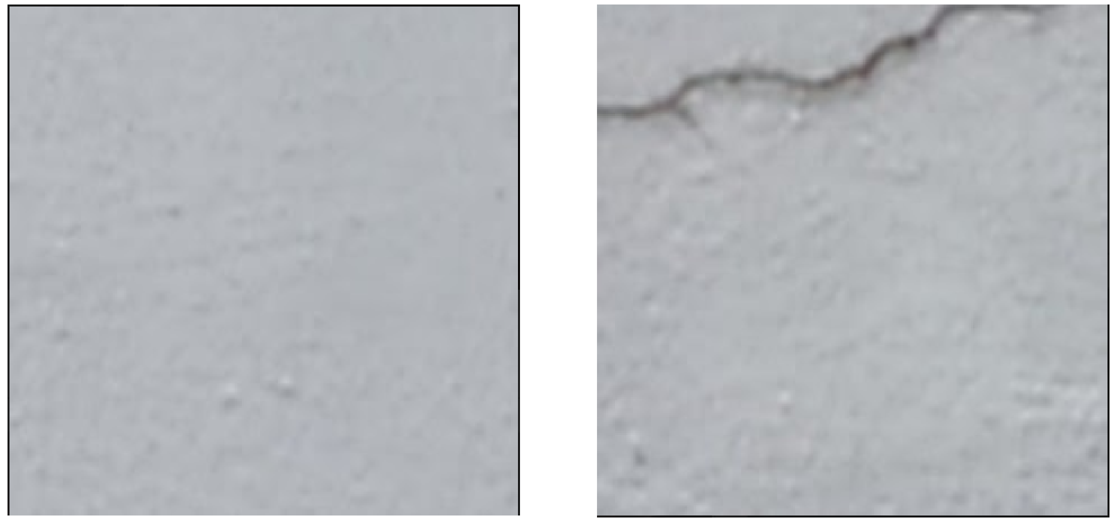
WAS THIS A FAIR BATTLE ?

THE "NO FREE LUNCH THEOREM"

CNN TRAINED



CNN SAW



REGION OF DAMPING DETECTION

A RUDIMENTARY APPROACH

GABOR FILTER USAGE

Fig 5.12 a) Original Image

Fig 5.12 b) After Gabor Filtering

GABOR FILTER USAGE

Fig 5.12 a) Original Image

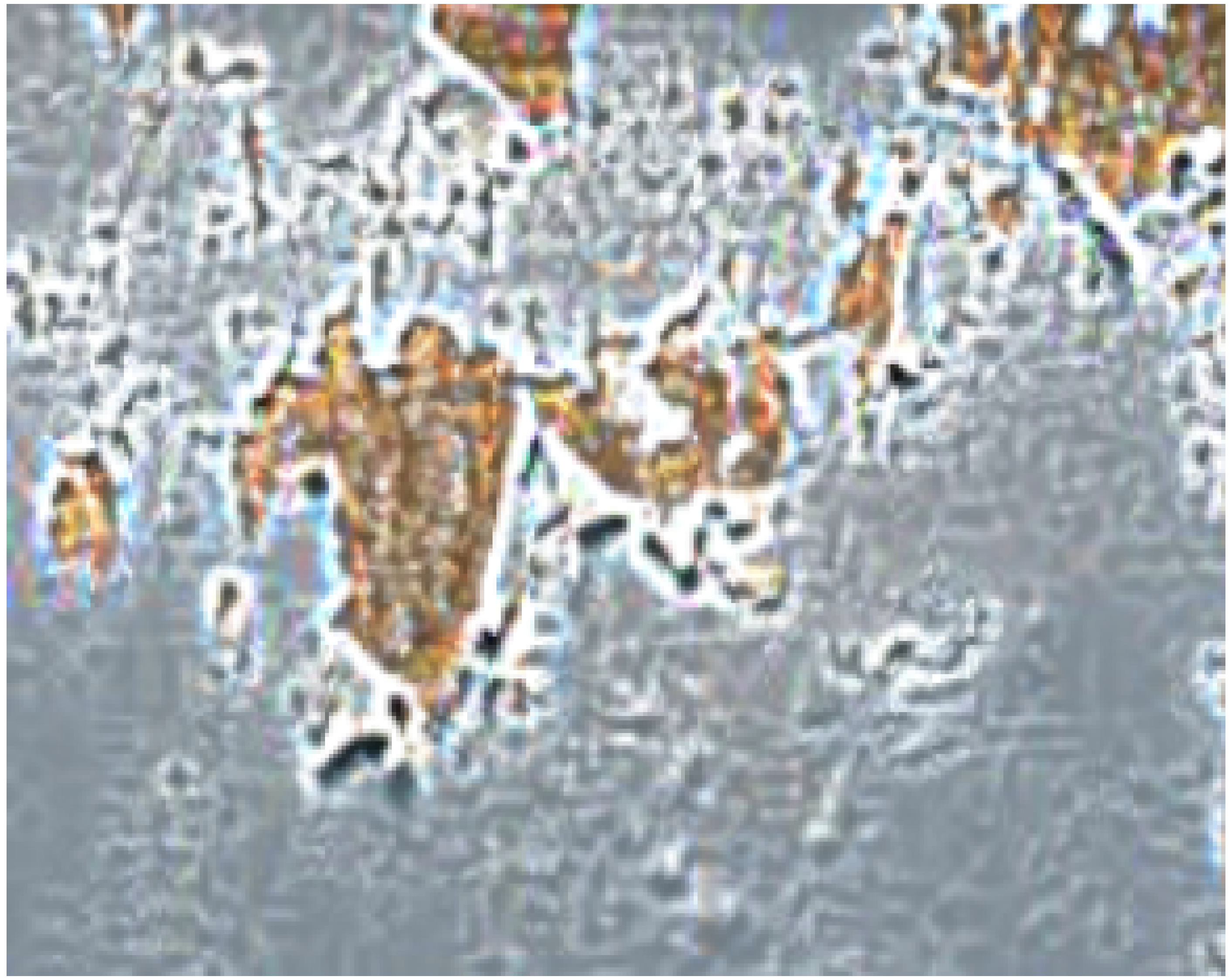


Fig 5.12 b) After Gabor Filtering

REGION OF DEFECTIVE PLASTERING DETECTION

A RUDIMENTARY APPROACH

THE EVIDENT DISTINCTION; MORE TO WORK ON THIS

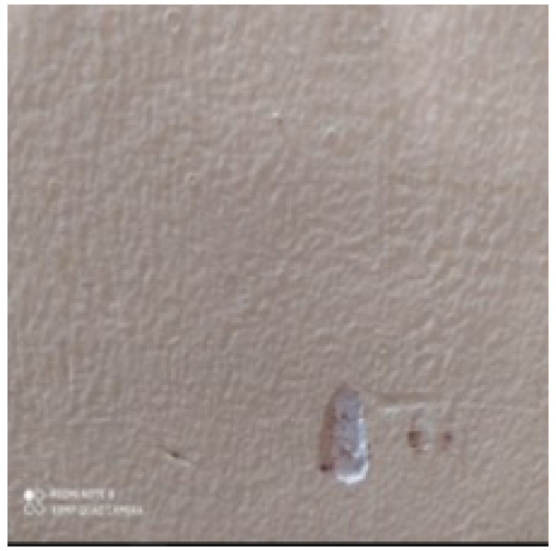


Fig 5.13 a) Defected Image

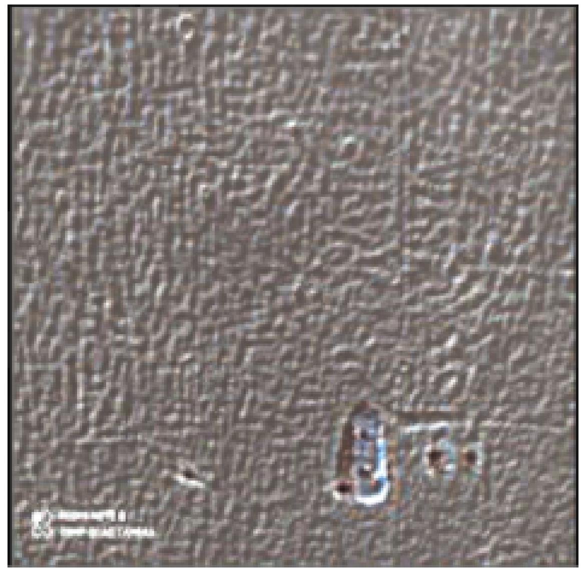


Fig 5.13 a) Defect Highlighted

Fig 5.15 a) No-defect Image

Fig 5.15 a) Nothing is highlighted

Fig 5.14 a) Defected Image

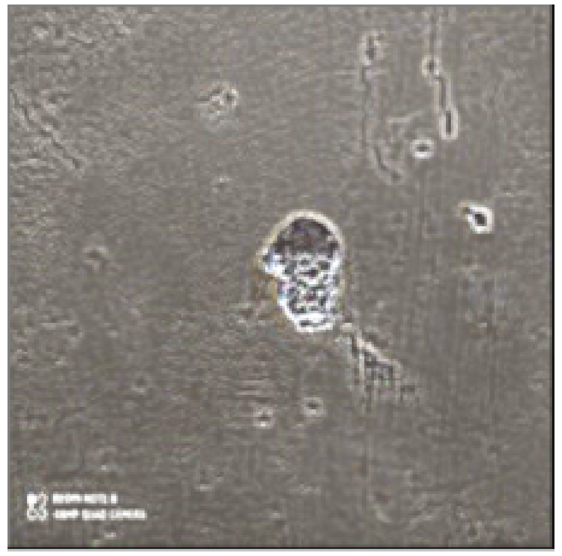


Fig 5.14 a) Defect Highlighted

Fig 5.16 a) No-defect Image

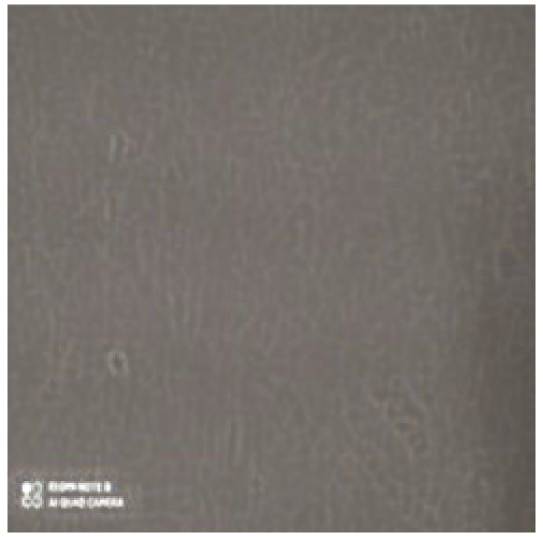


Fig 5.16 a) Nothing is highlighted

FUTURE ENHANCEMENTS

FUTURE SCOPE OF WORK

- Use **one-shot learning or zero-shot learning** to be able to classify defects easily without having too much training data
- Automate the ability of finding the **classification threshold** in the empirical method for crack detection
- Find better ways to classify cracks **based on their intensity**
- **Collect and create a dataset of images that have other defects** on buildings as there are almost no datasets like this. Almost all only have cracks.
- It can be noticed how pure DIP has produced some wonderful results. So, trying out **more techniques** such as sharpening before thresholding and other related techniques will definitely aid in better results. Maybe even produce a model that outperforms CNN!
- **Integrating our model** with hardware like a UAV will be an important step to be undertaken so that we can automate the whole process of detecting building damage

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THANK YOU !