# AIRCRAFT FUSELAGE DEFECT DETECTION USING DEEP NEURAL NETWORKS

TOUBA MALEKZADEH, MILAD ABDOLLAHZADEH
HOSSEIN NEJATI, NGAI-MAN CHEUNG

SINGAPORE UNIVERSITY OF TECHNOLOGY AND DESIGN (SUTD)

# Introduction

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- This paper makes contributions to the field of **automatic defect detection of an aircraft fuselage with image analysis techniques**.

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- **Aircraft inspection and maintenance** is an essential to safe air transportation.
- This paper makes contributions to the field of **automatic defect detection of an aircraft fuselage with image analysis techniques**.
- In recent years, **deep neural networks (DNN)** have shown promising results in different classification tasks.
- Although DNNs can be used to perform classification directly using the output of the last network layer, they can also be used **as a feature extractor combined with a classifier.**

# Our Contributions



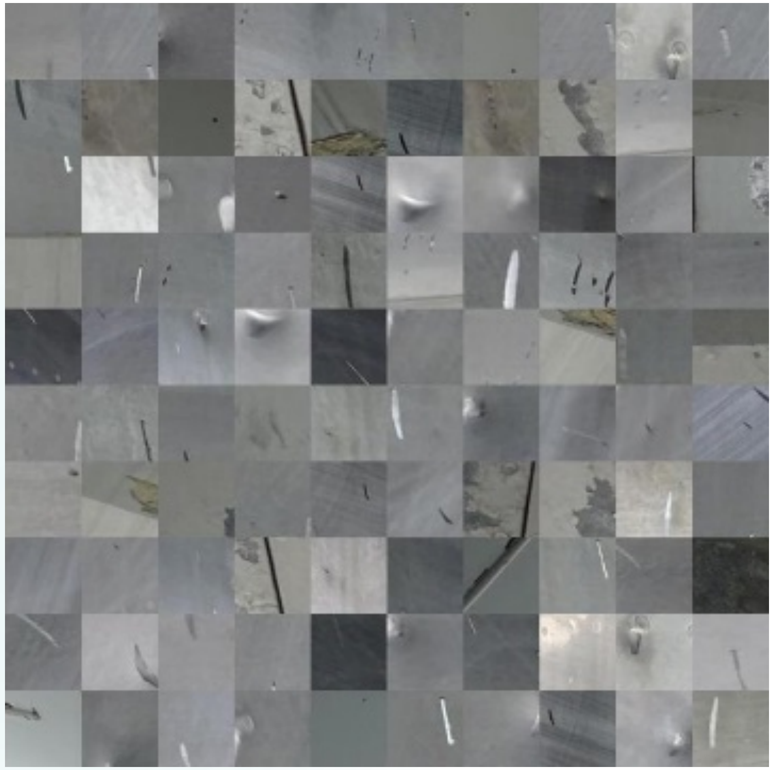
- In this paper, we investigate a classification system that employs a DNN, pretrained using natural images, to extract features for aircraft fuselage defect detection, where there are few samples available.
- The contributions of this study are:
  - *The first work for automatic defect detection of aircraft fuselage using visual images and deep learning.*
  - *A fast and accurate detection algorithm with selection of ROI using SURF interest points.*
  - *A technique to handle washed and unwashed fuselage based on pre- and post-processing.*

# Datasets

- Our dataset images are taken in a straight view of the airplane fuselage.
- During the inspection, a drone can be used to capture these images automatically.
- All images have three color channels and 3888×5184 resolution.


# Datasets

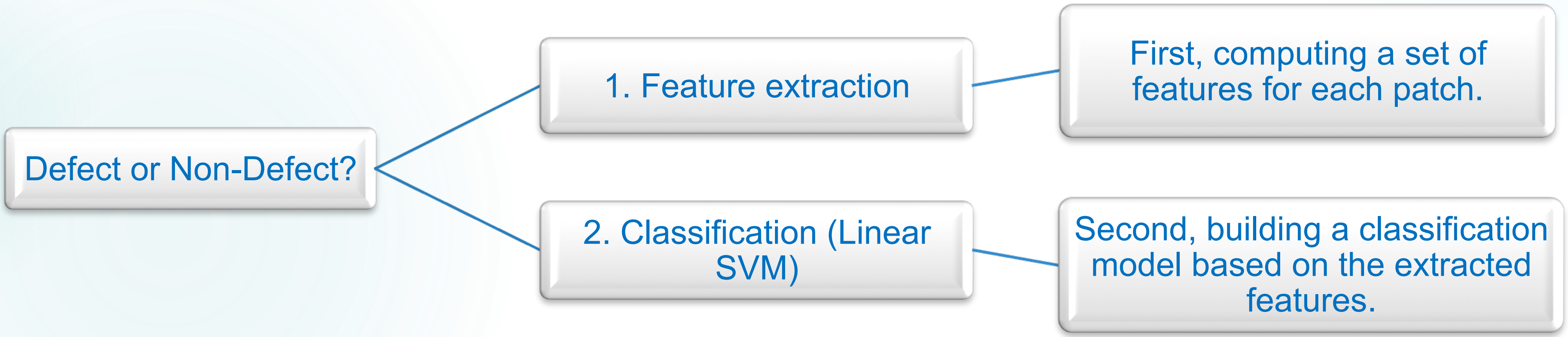
- Some examples of the defect(left) and no-defect(right) patches in our dataset:



# Methodology



- A *patch-based* scheme is used for detection of defects.
- Data is split into disjoint *training* and *testing* sets employing *K-fold* cross validation on the images rather than the patches to avoid *data leakage*.
- Each patch is classified into *defect or non-defect* class via a two-step process:



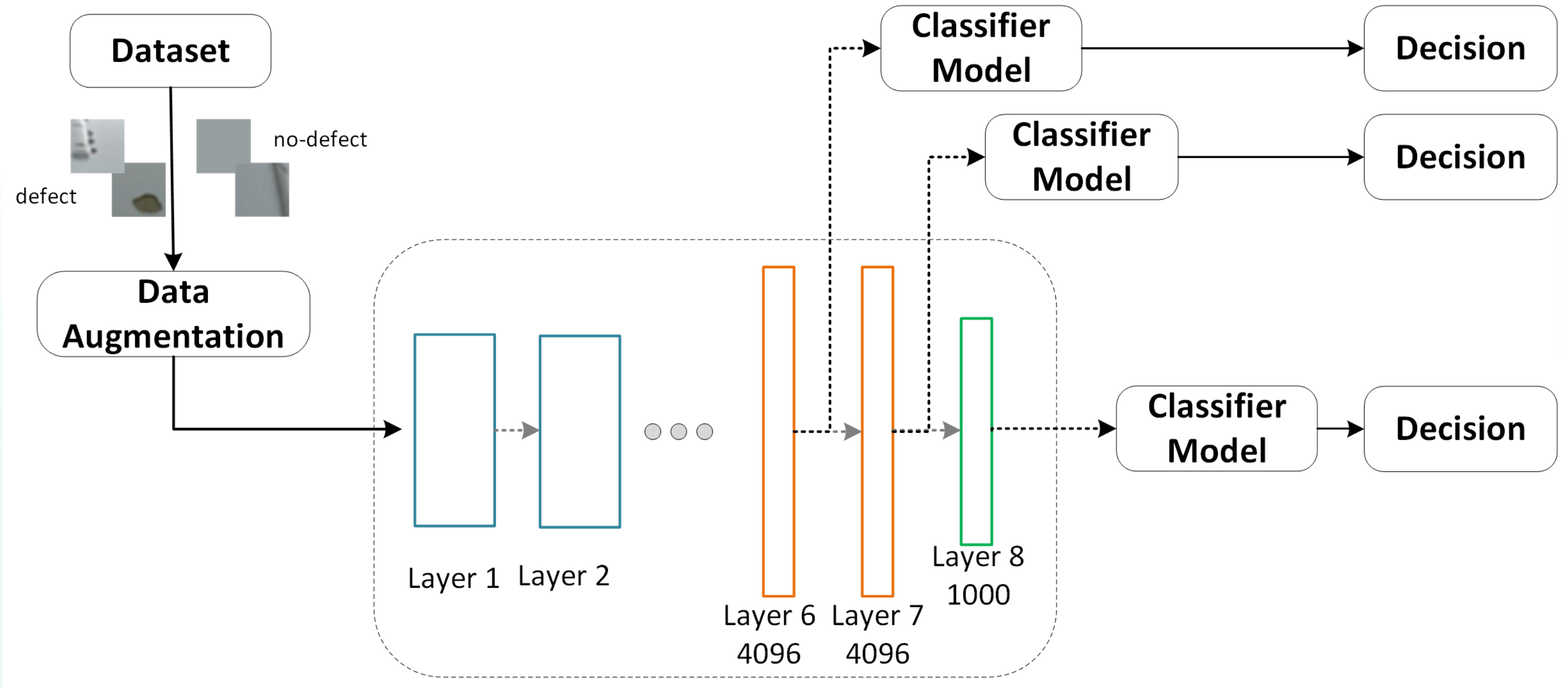
# Methodology



***Feature Extraction***

- Our experiments show, among different discriminative features, pretrained CNN results in the best performance.
- A CNN trained on ImageNet is used as feature extractor.
- Considering the limited size of our dataset, we propose to build a classifier model on top of the output (activations) of the hidden layers.

# Methodology




*Block diagram of the proposed method for defect detection*

# Methodology



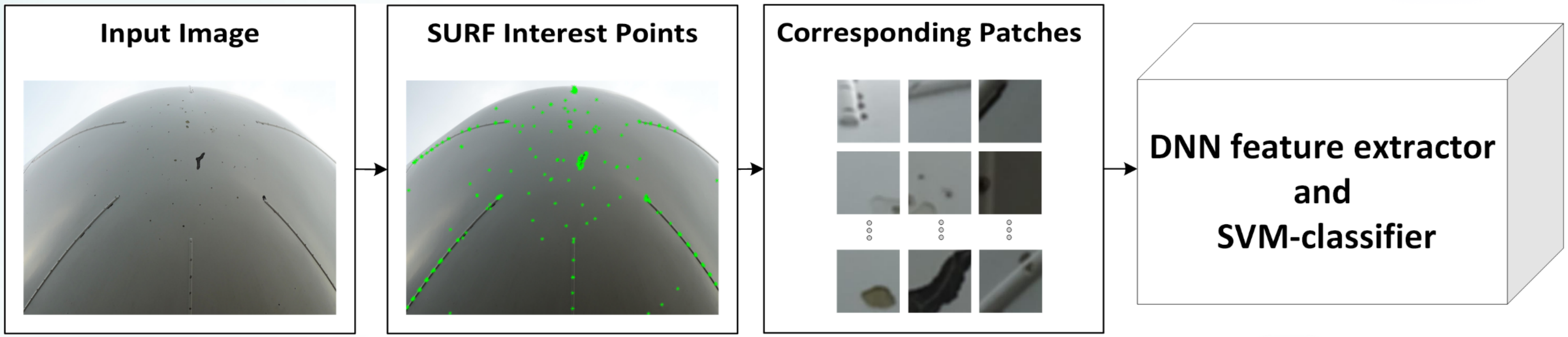
***Boosting Defect Detection***

- Too many input patches ➔ High processing time.
- Speed up the algorithm via enforcing the evaluation to some regions of interest.
- The ROI must include all the probable defect areas.
- We observe that ***Speeded up robust feature (SURF)*** is able to detect all the defect regions together with some normal regions which are similar to the defects.

# Methodology



- Apply *SURF interest point detector* to select some patches as candidates for evaluation procedure.
- A patch is included in the *defect evaluation procedure* if it contains at least one SURF interest point.
- Evaluating only the patches of the ROI ➔ Speed up the defect detection by <u>*6x*</u>.



# Methodology

***Post-processing***

- Washing status of the aircraft  affects the defect detection procedure.
- Unwashed aircraft with dirty spots on it ➔ misleads the defect detection.
- For an unwashed aircraft ➔ apply a low-pass Gaussian filter to reduce the noise-like spots on the fuselage images
  - Constraint ➔ To have minimum smoothing effect on the real defects.

# Results



- The average results of applying different feature descriptors on the data set
  - Feature extractor + Linear SVM

| Method | | Accuracy | Sensitivity | Specificity |
|---|---|---|---|---|
| **RGB histogram** | | 0.603722 | 0.295050 | 0.808990 |
| **HSV histogram** | | 0.602995 | 0.309751 | 0.798006 |
| **LBP** | | 0.603833 | 0.126360 | 0.921346 |
| **SURF** | | 0.636679 | 0.274245 | 0.846598 |
| **VGG-f** | $FC^6$ | **0.876236** | **0.854368** | 0.905322 |
| | $FC^7$ | 0.875025 | 0.849498 | 0.908975 |
| | $FC^8$ | 0.871628 | 0.848207 | 0.902778 |
| **AlexNet** | $FC^6$ | 0.847333 | 0.711691 | 0.937537 |
| | $FC^7$ | 0.846318 | 0.706273 | **0.939451** |
| | $FC^8$ | 0.834154 | 0.683291 | 0.934481 |

Proposed DNN methods

# Results



***Results of Testing on Unseen Images***

- Average performance of the proposed algorithm on a set of unseen images:

| Accuracy | Sensitivity | Specificity | Runtime (sec) |
|---|---|---|---|
| 0.963784 | 0.964891 | 0.963823 | 15.7874 |

- ‘fc6’ of VGG-f ➔ as feature extractor.
- Pretrained CNN model ➔ From MatConvnet library.

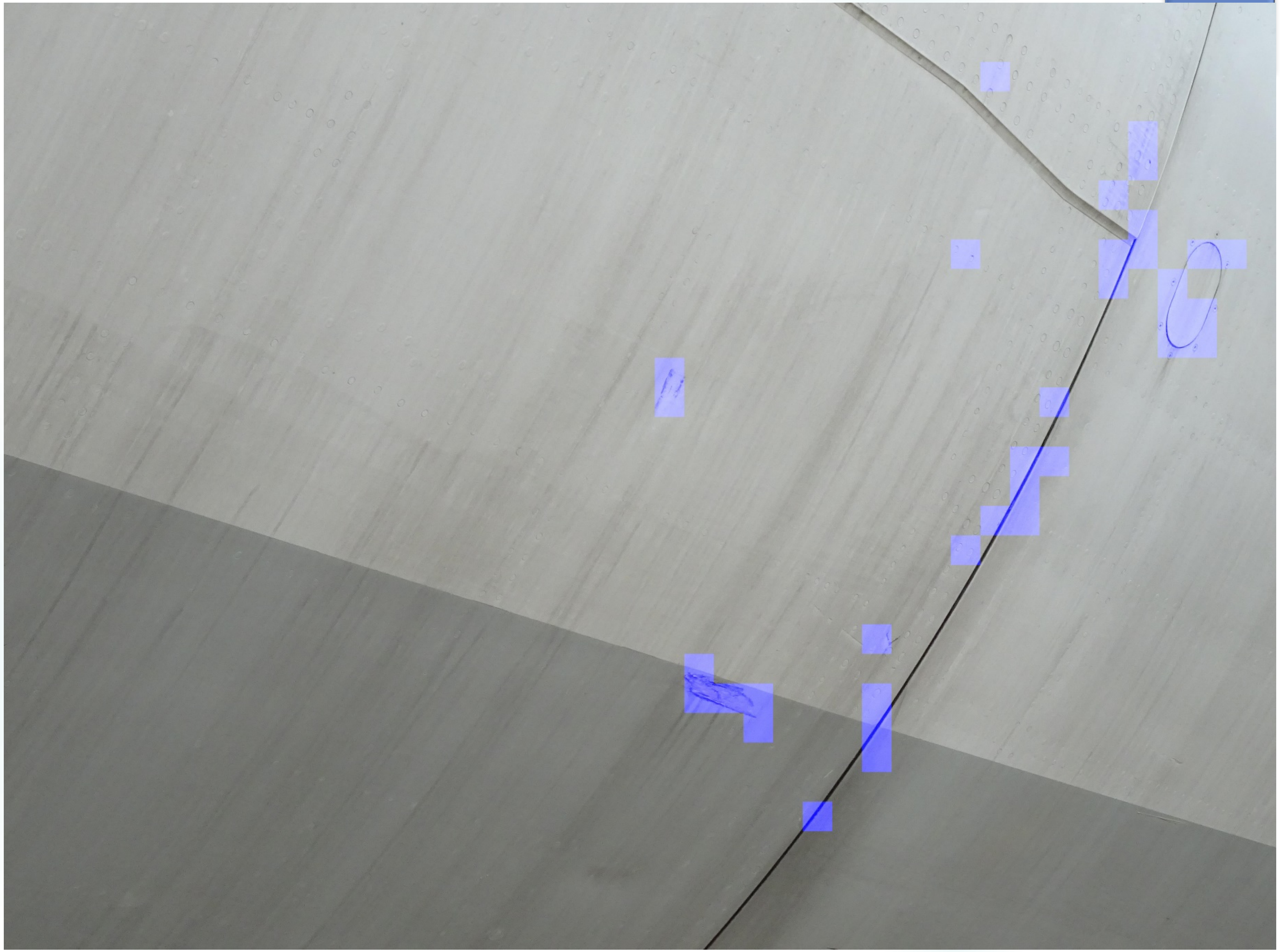
# Results



- **96.37%** accuracy ➔ only 3.63 % of the patches are misclassified.
- **96.48%** sensitivity ➔ 3.52% of the defect patches are missed.
  - **Every defect region is at least partially detected which means practically the system has located all defect regions.**
- **96%** specificity ➔ 4% of the whole airplane structure needs to be manually inspected by the worker.
- The average run time **15.78** seconds for high resolution image (on a laptop computer) ➔ enables efficient automatic inspection.

# Some examples:

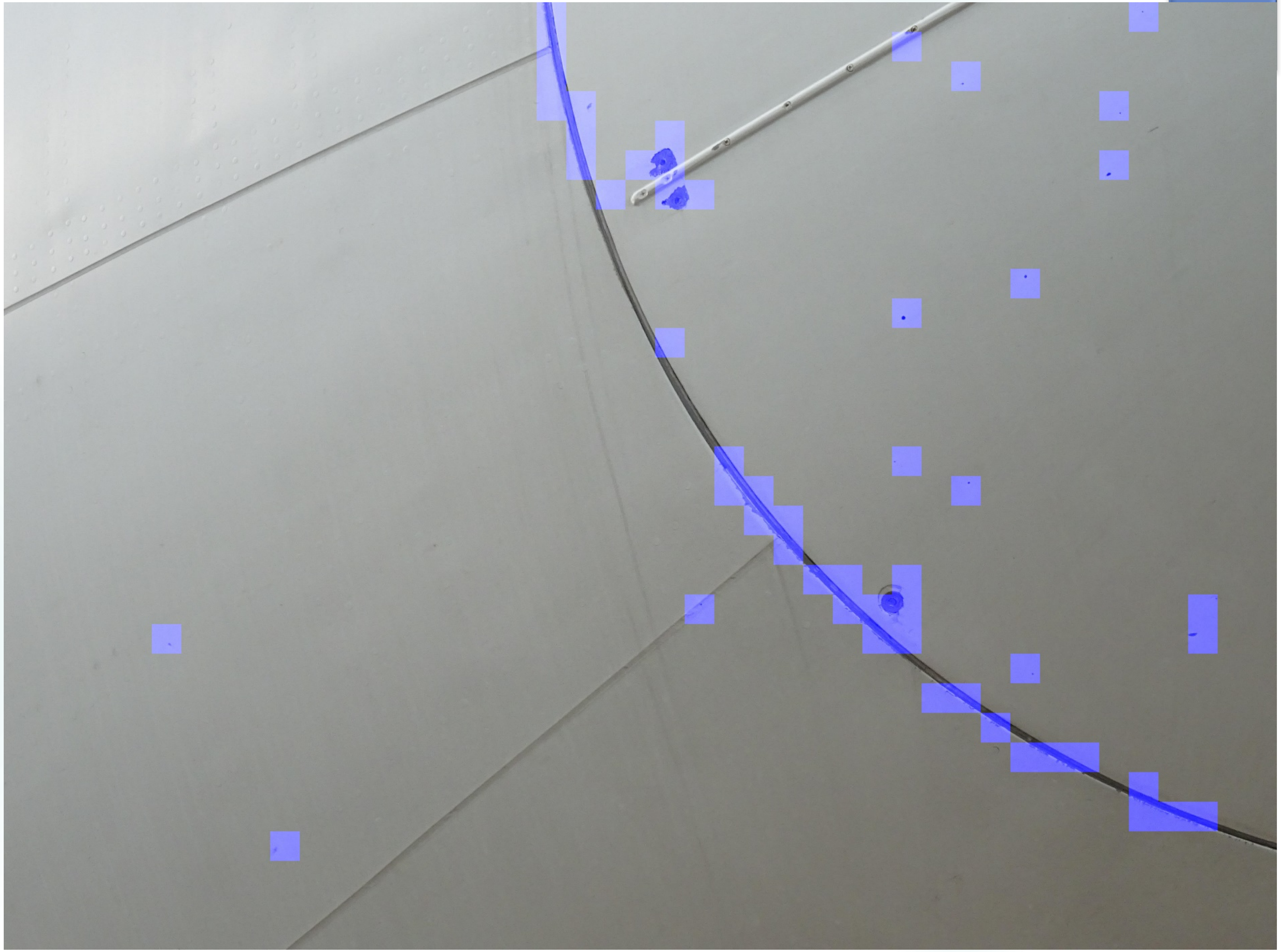
Accuracy:0.980378
Sensitivity:1.000000
Specificity:0.980263



# Some examples:



Accuracy:0.972384
Sensitivity:1.000000
Specificity:0.972079



# Conclusion



- Proposed an automatic aircraft fuselage defect detection method.
- Our proposed defect detection applies transferred features from pre-trained CNNs .
- Propose to speed up defect detection algorithm using ROIs detected by SURF.
- The proposed technology can detect almost all the defects of the aircraft fuselage, reducing the workload of manual inspection significantly.

- **Question: ngaiman_cheung@sutd.edu.sg**