SYSTEM DEVELOPMENT OF IMAGE DATA AUGMENTATION USING GENERATIVE ADVERSARIAL NETWORK (GAN)

This report is submitted in accordance with requirement of the University Teknikal Malaysia Melaka (UTeM) for Bachelor Degree of Manufacturing Engineering (Hons.)

by

LIM HOU HUA

B051810119

971111-13-6333

FACULTY OF MANUFACTURING ENGINEERING

2022

UTeM

اونيۏرسيتي تيكنيكل مليسيا ملاك

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

BORANG PENGESAHAN STATUS LAPORAN PROJEK SARJANA MUDA

Tajuk: **SYSTEM DEVELOPMENT OF IMAGE DATA AUGMENTATION USING GENERATIVE ADVERSARIAL NETWORK (GAN)**

Sesi Pengajian: **2021/2022 Semester 2**

Saya **LIM HOU HUA (971111-13-6333)**

mengaku membenarkan Laporan Projek Sarjana Muda (PSM) ini disimpan di Perpustakaan Universiti Teknikal Malaysia Melaka (UTeM) dengan syarat-syarat kegunaan seperti berikut:

1. Laporan PSM adalah hak milik Universiti Teknikal Malaysia Melaka dan penulis.
2. Perpustakaan Universiti Teknikal Malaysia Melaka dibenarkan membuat salinan untuk tujuan pengajian sahaja dengan izin penulis.
3. Perpustakaan dibenarkan membuat salinan laporan PSM ini sebagai bahan pertukaran antara institusi pengajian tinggi.
4. *Sila tandakan (√)

☐ SULIT (Mengandungi maklumat yang berdarjah keselamatan atau kepentingan Malaysia sebagaimana yang termaktub dalam AKTA RAHSIA RASMI

☑ TERHAD (Mengandungi maklumat TERHAD yang telah ditentukan oleh organisasi/ badan di mana penyelidikan dijalankan)

☐ TIDAK TERHAD

Disahkan oleh:

Alamat Tetap:
Lot 1923, Taman Lily,
95400 Saratok, Sarawak

Tarikh: 28 June 2022

Cop Rasmi:
DR. NUR AIDAWATY BINTI RAFAN
Timbalan Dekan (Akademik)
Fakulti Kejuruteraan Pembuatan
Universiti Teknikal Malaysia Melaka

Tarikh: 25 July 2022

*Jika Laporan PSM ini SULIT atau TERHAD, sila lampirkan surat daripada pihak berkuasa/organisasi berkenaan dengan menyatakan sekali sebab dan tempoh laporan PSM ini perlu dikelaskan sebagai SULIT atau TERHAD.

FAKULTI KEJURUTERAAN PEMBUATAN

BORANG PENGESAHAN TAJUK INDUSTRI BAGI PROJEK SARJANA MUDA

Tajuk PSM: System development of image data augmentation using Generative Adversarial Network

Nama Syarikat: ViTrox Technologies Sdn Bhd

Sesi Pengajian: 2021/2022

Adalah saya dengan ini memperakui dan bersetuju bahawa Projek Sarjana Muda (PSM) yang bertajuk seperti di atas adalah merupakan satu projek yang dijalankan berdasarkan situasi sebenar yang berlaku di syarikat kami sepertimana yang telah dipersetujui bersama oleh wakil syarikat kami dan penyelia serta pelajar dari Fakulti Kejuruteraan Pembuatan, Universiti Teknikal Malaysia Melaka yang menjalankan projek ini.

Tandangan Wakil Syarikat:

Cop Rasmi: ViTrox Technologies Sdn. Bhd. 907043-D

Nama Pegawai: Yeoh Siew Eng

Jawatan: Sr. Manager of People Management

Tarikh: 23 Dec 2021

Tandatangan Pelajar:

Nama Pelajar: Lim Hou Hua

No Matriks: B051810119

Tarikh: 08/12/2021

Tandatangan Penyelia:

Cop Rasmi: DR. NUR AIDAWATY BT RAFAN
Senior Lecturer
Fakulty of Manufacturing Engineering
Universiti Teknikal Malaysia Melaka
76100 Durian Tunggal, Melaka

Nama Penyelia: Dr Nur Aidawaty Bt Rafan

Jawatan: Pensyarah Kanan

Tarikh: 11 January 2022

DECLARATION

I hereby, declared this report entitled "System Development of Image Data Augmentation using Generative Adversarial Network (GAN)" is the result of my own research except as cited in references.

Signature : ....

Author's Name : LIM HOU HUA

Date : 28 June 2022

APPROVAL

This report is submitted to the Faculty of Manufacturing Engineering of Universiti Teknikal Malaysia Melaka as a partial fulfilment of the requirement for Degree of Manufacturing Engineering (Hons). The member of the supervisory committee is as follow:

....

(DR. NUR AIDAWATY BINTI RAFAN)

DR. NUR AIDAWATY BINTI RAFAN
Timbalan Dekan (Akademik)
Fakulti Kejuruteraan Pembuatan
Universiti Teknikal Malaysia Melaka

ABSTRAK

Sebuah projek dicadangkan untuk menyiasat kegunaan Generative Adversarial Netowork (GAN) untuk menambah data imej demi mengatasi masalah kelas tidak seimbang dalam klasifikasi wafer silikon yang mempunyai kecacatan calar. Masalah kelas tidak seimbang ini disebabkan oleh bilangan sampel rosak yang kecil berbanding bilangan sampel yang elok dalam pembuatan. Mask GAN telah digunakan untuk menghasilkan imej label daripada input kotak sempadan. Seterusnya, imej label dimasukkan kepada Defect Image GAN untuk "melukis" kecacatan pada imej input yang elok. Kebolehlaksanaan system telah dikaji dengan mengukur ketepatan algoritma pembelajaran mesin yang dilatih dengan data janaan GAN. Di samping itu, rangkaian saraf yang dilatih dengan data janaan GAN dan data janaan kaedah konvensional telah dibanding. Sistem yang dicadangkan telah diuji dengan McNemar's Test pada nilai keyakinan 95% dan menghasilkan peningkatan yang ketara berbanding kaedah konvensional.

ABSTRACT

A project is proposed to investigate the use of Generative Adversarial Networks (GAN) to augment image data to overcome class imbalance problems in silicon wafer microcrack defect classification. This class imbalance problem is due to the small number of defective products compared to non-defective products in a production environment. A Mask GAN is used to generate images of defect mask label when bounding box information is supplied. The artificial defect masks are used by a Defect Image GAN to “paint” defects onto non-defect images. The system's feasibility is analyzed by evaluating the accuracy of the classifier trained on the augmented data, along with the number of misclassified images of defective products. Two identical classifier networks are trained on traditionally augmented data and GAN-augmented data and be compared. The system is shown with McNemar’s test with a confidence of 95%, to produce a significant improvement over conventional methods.

DEDICATION

Dedicated to the joy of my family, Dolly.

ACKNOWLEDGEMENT

A thousand thank you to those who motivate, support and guide me along the journey of my final year project. I would first like to thank my final year project supervisor Dr. Nur Aidawaty binti Rafan who is always enthusiastic in providing guidance to our final year project group. Furthermore, I am grateful to have Dr. Zamberi bin Jamaludin, Dr. Shariman bin Abdullah, and Dr. Nazmin bin Mazlan for providing valuable insights in my thesis evaluation. In addition, I thank Mr. Lee Choon Teck and all my acquaintances at ViTrox who inspire me to further my interest in machine vision. Moreover, special thanks to all my friends who are there by my side and going through the challenges of studying during this pandemic period together. Finally, I offer my deepest appreciation to my family without whom I will never be where I am today.

TABLE OF CONTENTS

ABSTRAK		i
ABSTRACT		ii
DEDICATION		iii
ACKNOWLEDGEMENT		iv
TABLE OF CONTENTS		v
LIST OF TABLES		viii
LIST OF FIGURES		ix
LIST OF ABBREVIATIONS		xi
CHAPTER 1: INTRODUCTION		
1.1	Project Background	1
1.2	Problem Statement	3
1.3	Objectives	4
1.4	Scope	4
1.5	Project Rationale	5
1.6	Project Methodology	5
1.7	Thesis Organization	7
CHAPTER 2: LITERATURE REVIEW		
2.1	Image Classification Problem	8
	2.1.1 Image Classification Pipeline	9
	2.1.2 Machine Learning-based Classification	10
2.2	Deep Neural Networks	11
	2.2.1 Network Architecture	11
	2.2.2 Activation Functions	12
	2.2.3 Loss Function	12
	2.2.4 Backpropagation and Optimization	13
	2.2.5 Regularization and Normalization	13
2.3	Convolution Neural Networks (CNN)	14
	2.3.1 Convolution Operation	15
	2.3.2 Common CNN used for Classification	16
2.4	Image Data Augmentation Methods	17

2.5 Generative Adversarial Networks (GAN) 18
2.5.1 GAN Framework 18
2.5.2 Deep Convolution GAN (DCGAN) 19
2.5.3 Conditional GAN 19
2.5.4 MSG-GAN 20
2.5.5 Sequential Image Generation using GAN 21
2.6 Deep Learning Methodology 22
2.6.1 Transfer Learning 22
2.6.2 Model Validation 22
2.6.3 Model Selection 23
2.6.4 Performance Metric 24
2.6.5 Software 25
2.7 Related Works 26

CHAPTER 3: METHODOLOGY
3.1 Project Overview 27
3.2 Design of Experiment 30
3.3 Project Software and Tools 31
3.3.1 Programming Language, Libraries and Platform 31
3.3.2 Transfer Learning 31
3.3.3 Data Source 32
3.3.4 Neural Network Configuration 33
3.3.5 Conventional Data Augmentation Methods 34
3.3.6 Performance Evaluation Metric 34

CHAPTER 4: RESULTS AND DISCUSSIONS
4.1 GAN Image Generation 35
4.1.1 Mask GAN Output 35
4.1.2 Defect GAN Output 36
4.2 Classifier Performance Analysis 37
4.2.1 Rotate and Flip Augmented Data 37
4.2.2 GAN-Augmented Data 38
4.2.3 McNemar's Test 39
4.2.4 Loss Curve 40

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS
5.1 Conclusion 41
5.2 Recommendations 41

5.3 Sustainability of Project 42
5.4 Project Complexity 42
5.5 Basic Entrepreneurship 42

REFERENCES **43**

APPENDICES **50**

LIST OF TABLES

Table 2.1: Example of Four Common Activation Functions 12
Table 2.2: Common CNN Architectures used in Research 16
Table 2.3: Comparison of Data Augmentation Effect on CNN Performance (Taylor & Nitschke, 2018) 17
Table 2.4: Performance Metric of Classification Model 24
Table 2.5: Performance Metric of GAN 24
Table 2.6: Summary of Related Works 26

Table 3.3: Conventional Data Augmentation Methods Used. 34
Table 3.4: Performance Metrics Used 34

LIST OF FIGURES

Figure 1.1: Architecture of a Typical GAN from (An Intuitive Introduction to Generative Adversarial Networks (GANs), 2018) 2
Figure 1.2: Visualization of the Class Imbalance Problem in Classification (Kushwaha, 2019). 3
Figure 1.3: Overview of Project 5
Figure 1.4: Flow Chart of the Proposed Project 6

Figure 2.1: Samples from insect classification dataset (Wu et al., 2019). 8
Figure 2.2: Workflow of Supervised Learning (A. Zhang et al., 2021) 10
Figure 2.3: Example of Simple Feedforward Neural Network (Goodfellow et al., 2016) 11
Figure 2.4: Example of Convolutional Neural Network Architecture (Vasan et al., 2020). 14
Figure 2.5: Moving 3x3 Filter Across Image to Detect Features (Glassner, 2021). 15
Figure 2.6: Overview of GAN Framework (Harada et al., 2019). 18
Figure 2.7: Framework of Conditional GAN (Mirza & Osindero, 2014) 19
Figure 2.8: Overview of MSG-GAN architecture 20
Figure 2.9: Overview of Sequential Image Generation GAN 21
Figure 2.10: Illustration of 10-fold Cross Validation (Berrar, 2018). 23
Figure 2.11: Symbol of Python and Google Colab (Parmar, 2021). 25
Figure 2.12: Symbol of Pytorch (left) and Tensorflow (right) (*PyTorch vs TensorFlow*, 2021). 25

Figure 3.1: Project Planning 29
Figure 3.2: Experiment Tree of the Project 30
Figure 3.3: Flowchart of Transfer Learning and Fine Tuning. 31
Figure 3.4: Microcrack Defect Samples from ViTrox. 32
Figure 3.5: Configuration of proposed system 33

Figure 4.1: Output of Mask GAN 35

Figure 4.2: Output of Defect Image GAN 36
Figure 4.3: Confusion Matrix of Classifier trained on Rotate and Flip Augmented Data 37
Figure 4.4: Images that produce False Negative results in Classifier trained on Rotate and Flip Augmented Data 37
Figure 4.5: Confusion Matrix of Classifier trained on GAN-Augmented Data 38
Figure 4.6: McNemar's Test Matrix of Classifier trained on GAN-Augmented Data and Rotate and Flip Augmented Data 39
Figure 4.7: Loss Curve of Classifier trained on data augmented with both methods 40

LIST OF ABBREVIATIONS

CNN	Convolutional Neural Network
DCGAN	Deep Convolutional GAN
FID	Fréchet Inception Distance
GAN	Generative Adversarial Network

CHAPTER 1

INTRODUCTION

1.1 Project Background

This project is performed in collaboration with ViTrox Technologies Sdn. Bhd. ViTrox specializes in developing automated vision inspection system. Machine learning algorithms applied in their machine vision solutions aids their customers to ensure quality in their customer's production.

The presence of microcracks is one of the defects in silicon wafers. Microcrack refers to cracks with a thickness that is on the scale of micrometers. This type of defect is hard to be seen through the naked eye. Hence, computer vision-based solutions are the go-to in detecting microcracks in silicon wafers.

Image-based defect detection is a challenging problem requiring high accuracy algorithms and is often tackled using machine learning techniques. Deep convolutional neural networks are ubiquitous in image classification problems as they can produce results with high accuracy. In addition, convolutional neural networks effectively extract image features while numerous layers in deep neural networks greatly improve network performance by efficiently leveraging large amounts of training data (Krizhevsky et al., 2017).

Data augmentation is the process of manipulating training data to achieve better generalization. Common techniques in image data augmentation are "handcrafted", which include geometric transformations and noise filters (Shorten & Khoshgoftaar, 2019).

GAN is a framework of training two or more neural networks in a contest against each other to generate data that follows the distribution of the training set (Goodfellow et al., 2014). As seen in Figure 1.1, GAN consists of a generator network and a discriminator network. A generator network takes in random noise as input and produces images that mimic the training data. Meanwhile, a discriminator network is trained to distinguish between real and generated data. Iterations of training will result in both networks being more competent in their tasks, eventually producing generated data that closely resemble the training data. Hence, it is easy to see the implication of applying GAN in image data augmentation (Su, 2021).

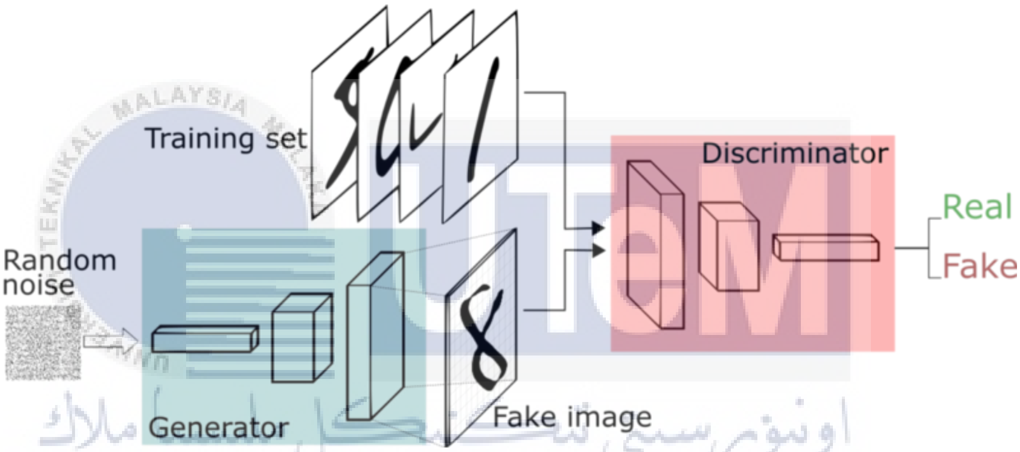

Figure 1.1: Architecture of a Typical GAN from (An Intuitive Introduction to Generative Adversarial Networks (GANs), 2018)

1.2 Problem Statement

In defect classification problems, non-defective samples are usually more abundant than defective samples. This phenomenon is also known as the class imbalance problem. As a result, the distribution of the minority class will be misrepresented, and the number of false negatives will increase (Buda et al., 2018). As seen in Figure 1.2, classifiers trained on imbalanced data tend to misclassify the minority class.

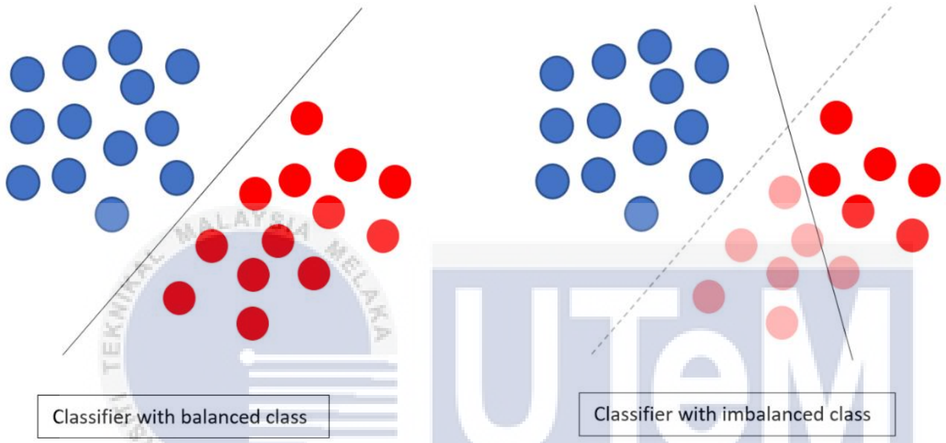

Figure 1.2: Visualization of the Class Imbalance Problem in Classification (Kushwaha, 2019).

Furthermore, misclassification of defective products as being non-defective is critically detrimental in defect detection applications. Data augmentation can be used to balance the data distribution while increasing data size. While the traditional "handcrafted" data augmentation technique is viable, it is specific to the image source and has to be manually tuned for each different source of the image. Hence, GAN is proposed as a generalizable solution to augment the minority samples and balance the data distribution.

1.3 Objectives

The project objectives are as follows:

(a.) To produce a generalizable image data augmentation system for defect detection problems using GAN.

(b.) To improve the accuracy of neural network-based defect detection algorithm by data augmentation using GAN.

(c.) To analyze the impact of GAN-based data augmentation and traditional data augmentation on the performance of classification networks.

1.4 Scope

The project scopes are as follows:

a. The proposed system will be evaluated on an image-based defect detection problem.

b. Transfer learning will be used in training the classification network and GAN to avoid training the networks from scratch.

c. Image under different conditions will be used to evaluate the generalizability of the proposed system.

d. Traditional data augmentation techniques, including noise injection and geometric transformation, will be used as a benchmark for comparison in evaluating the performance of GAN-based data augmentation.

e. The number of misclassified defective images by the classifier trained with augmented data will be used as a metric for the performance of the GAN.

1.5 Project Rationale

The project rationale are as follows:

a. Data with imbalance class problem tend to affect machine learning model performance. This project aims to use data augmentation to overcome class imbalance by artificially generating samples of the minority class.

b. Conventional data augmentation methods are chosen based on the characteristics of the input samples. GAN is proposed to automate the data augmentation step by learning image characteristics and generating artificial samples that are similar to input data.

1.6 Project Methodology

The project consists of using GAN as an alternate method of data augmentation. The role of GAN within the overall machine learning framework is shown in Figure 1.3.

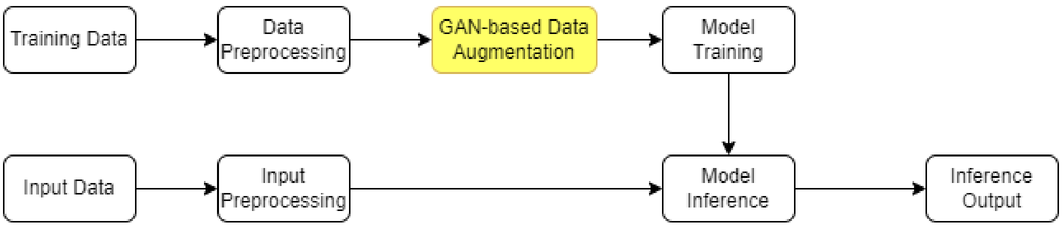

Figure 1.3: Overview of Project

Furthermore, the overall methodology of the project is summarized in the flowchart in Figure 1.4.

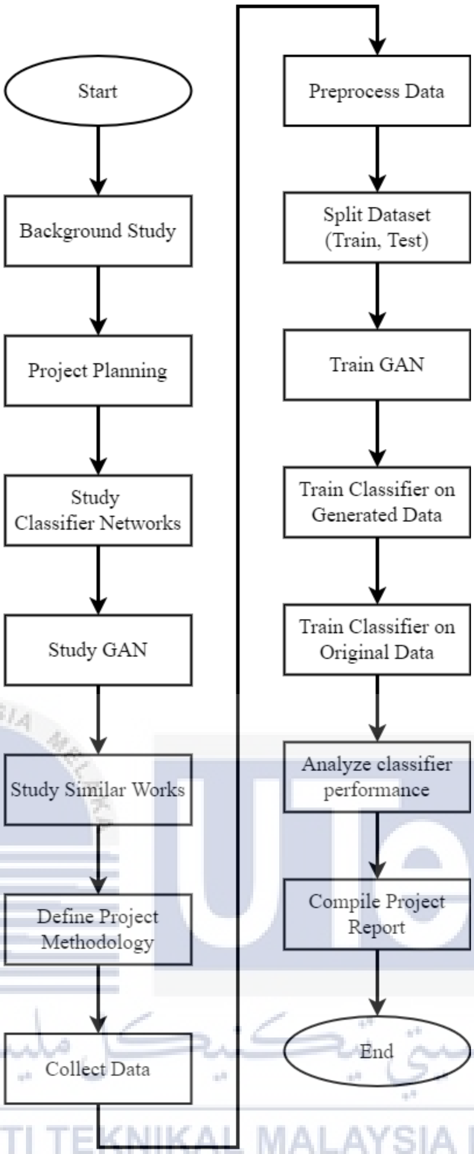

Figure 1.4: Flow Chart of the Proposed Project

After a preliminary background study is performed, an experiment will be conducted to evaluate the proposed system. First, image data collected and preprocessing such as resizing of the image will be done. The data will then be split into training and testing sets. Further, the training data will be be used to train the GAN-based data augmentation system. Afterwards, two classifiers will be trained, with traditionally augmented data and GAN-augmented data. Finally, the rate of false negatives by these two classifiers will be compared to show the viability of GAN-based data augmentation.

1.7 Thesis Organization

This thesis is organized according to the 5 main chapters. Chapter 1 describes the project background, problem statement, objectives, scope, and rationale. Furthermore, literature on GAN and machine learning frameworks are reviewed in Chapter 2. In addition, project planning and experiment procedure is detailed in Chapter 3. Moreover, Chapter 4 analyzes results obtained from the experiments. Finally, the project is concluded in Chapter 5.

CHAPTER 2

LITERATURE REVIEW

2.1 Image Classification Problem

Image classification is a class of machine learning problem that involves taking in an image as input and determining the class that the image belongs to (Russakovsky et al., 2015). For example, insect image classification involves determining the type of insect in each image within the dataset, as shown in Figure 2.1.

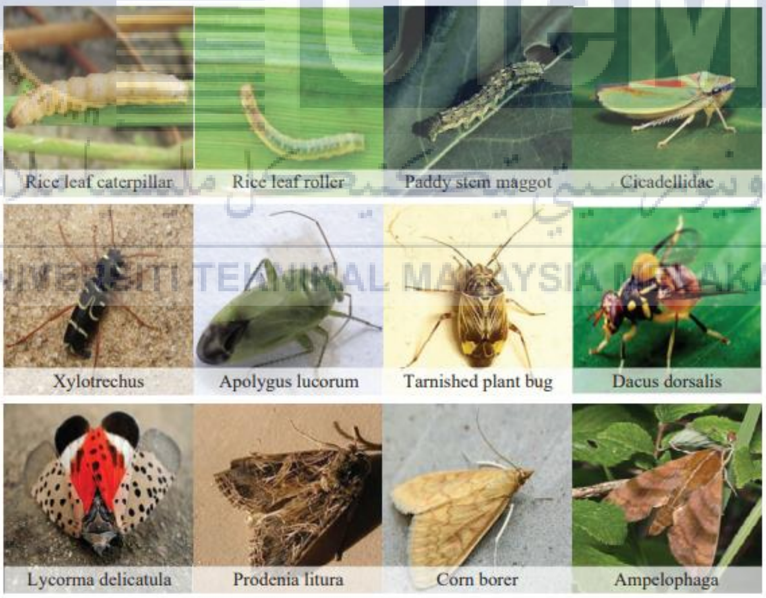

Figure 2.1: Samples from insect classification dataset (Wu et al., 2019).