AUTOMATED VISUAL DETECTION OF EXTERNAL WELDING DEFECT USING EMBEDDED MACHINE LEARNING

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DEDICATION

To my family who loves me, especially to my beloved mother and father for education and their support. Not to be missed my partner, who motivates and together through the up and down of this journey.

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ABSTRACT

This project is designed to perform a quality check on a welded material's surface. Welding is the most useful process for joining materials in the manufacturing, automotive, and construction industries. As a result, in order to meet a client requirements, all welding works must be inspected, with the most basic method is non-destructive visual inspection testing. Surface inspection can be performed using non-destructive methods such as dye-penetration testing and magnetic particle inspection. However, those methods are expensive, take a long time to complete inspections, and require a complex procedure to operate. This project proposed an automated visual inspection system that relies on embedded machine learning. This system is made up of a camera, a microcontroller, and web server. The camera-based system will detect any defects on the welded material, which will then be processed by the microcontroller before being displayed on the web server through Wi-Fi connection. As a result, this system was split into two parts: software and hardware. The Arduino IDE was used to programme the system, and Edge Impulse was used to develop the embedding machine learning model. This system's hardware consists only ESP32-CAM module. As a result, it is possible to create an automated system that is user friendly and has simple operation procedure. Furthermore, a low-cost system with a short inspection time have been developed. A sharp and clear image with single type of defect appear on the workpiece help to provide best performance of defect classification. However, most likely same image captured, e.g. good welding and overlap defect, decrease the effectiveness of detection. The detection accuracy of this system can reach up to 95% with more training data provided, as for this project each defects detection accuracy are falls between 75 - 94 percent. In conclusion, the use of embedded machine learning in non-destructive testing is successful for the visual inspection method.

ABSTRAK

Projek ini direka bentuk untuk melakukan pemeriksaan kualiti pada permukaan bahan yang dikimpal. Kimpalan ialah proses yang paling berguna untuk menyambung bahan dalam industri pembuatan, automotif dan pembinaan. Akibatnya, untuk memenuhi keperluan pelanggan, semua kerja kimpalan mesti diperiksa, dengan kaedah yang paling asas iaitu ujian pemeriksaan visual tanpa merosakkan. Pemeriksaan permukaan boleh dilakukan menggunakan kaedah tanpa merosakkan seperti ujian penembusan pewarna dan pemeriksaan zarah magnetik. Walau bagaimanapun, kaedah tersebut mahal, mengambil masa yang lama untuk menyelesaikan pemeriksaan, dan memerlukan prosedur yang kompleks untuk beroperasi. Projek ini mencadangkan sistem pemeriksaan visual automatik yang bergantung pada pembelajaran mesin terbenam. Sistem ini terdiri daripada kamera, mikrokontroler, dan laman sesawang. Sistem berasaskan kamera akan mengesan sebarang kecacatan pada bahan yang dikimpal, yang kemudiannya akan diproses oleh mikrokontroler sebelum dipaparkan pada laman sesawang melalui sambungan Wi-Fi. Akibatnya, sistem ini dibahagikan kepada dua bahagian: perisian dan perkakasan. Arduino IDE diguna untuk memprogramkan sistem, dan Edge Impulse digunakan untuk membangunkan model pembelajaran mesin terbenam. Perkakasan sistem ini hanya mengandungi modul ESP32-CAM. Hasilnya, adalah mungkin untuk mencipta sistem automatik yang mesra pengguna dan mempunyai prosedur operasi yang mudah. Tambahan pula, sistem kos rendah dengan masa pemeriksaan yang singkat telah dibangunkan. Imej yang tajam dan jelas dengan satu jenis kecacatan muncul pada bahan kerja membantu memberikan prestasi klasifikasi kecacatan terbaik. Walau bagaimanapun, kemungkinan besar imej yang sama ditangkap, cth. kimpalan yang baik dan kecacatan pertindihan, mengurangkan keberkesanan pengesanan. Ketepatan pengesanan sistem ini boleh mencapai sehingga 95% dengan lebih banyak data latihan yang disediakan, kerana bagi projek ini setiap ketepatan pengesanan kecacatan adalah antara 75 - 94 peratus. Kesimpulannya, penggunaan pembelajaran mesin terbenam dalam ujian tanpa merosakkan berjaya untuk kaedah pemeriksaan visual.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Networks
CNN	Convolutional Neural Network
DNN	Deep Neural Network
EML	Embedded Machine Learning
ML	Machine Learning

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Problem Background

Welding is a common activity in many industries such as automotive, manufacturing, constructions, and aerospace. Welding activities is a fabrication process that joint material, usually metals or thermoplastics, where this process uses high heat melt the parts together and allowing them to cool, cause fusion. On top of that, filler material is added to the joint to form a pool of molten material that cools to form a joint.

Every fabrication process required quality control, this is where quality inspection plays an important role to detect any defects or crack of the welded joints. Conventionally, visual inspection was the commonly methods used in many industries, as it is the simplest and practical non-destructive test to observe the surface defects with the naked eyes or with the aid of magnifying glass. However, there are some limitations on visual inspection such as only applicable for surfaces detection, clearly detect on large defect and required professional inspector that major in welding, otherwise it is high probability to misinterpret the type of defects.

Nowadays, as an alternative or improvement for the conventional method, there are several non-conventional methods that have been proposed by other researchers such as ultrasonic, radiographic, eddy-current, and magnetic particles inspection. Using non-conventional methods may help inspector's task become easy, effective and precise to determine type of welding defects, but there are other limitations faced by the non-conventional methods, i.e. the equipment are expensive, large in size, less accuracy for surface detection, and required high skilled inspector to operated.

1.2 Problem Statement

Welding is a common activity used in the fabrication process. This process joints two or more parts that are fused together due to heat and pressure. It is easy to detect the quality of a welding work by identifying is there any surface defects that occurred. Therefore, visual inspection is the easier way to inspect the defects but this method are limited to large defect that are only obvious can be seen by naked eye and at some point the type of defect might be misinterpreted by the inspector.

However, there are several ways to detect surface defects. Dye-penetration method can check the defects by applying penetrant and developer. This method of welding inspection requires inspector to perform pre-cleaning on the welded surface then apply penetrant on the surface. After 20 – 30 minutes, the penetrant has "dwell-time'" to soak into the defects. The penetrant needs to be clean before apply developer solution, then the developer draws penetrant from defect out onto the surface. On top of that, this method is high cost and required long time to complete the inspection.

1.3 Research Objectives

There are three objectives of this research, as stated below:

(a) To develop visual detection system and embedded machine learning that can be used to detect external welding defects.

(b) To analyze the performance of surface welding defect detection.

(c) To implement the system for real surface welding defect detection.

1.4 Research Scope

The scope of this project is to carry out study on defect produced by the welding process. A dataset of photos for type of surface defects (cracks, porosity, overlap, spatter and undercut) is obtained by taking photos of welding on actual test pieces. A program with embedded machine learning (EML) capabilities will then be used to build a comparison technique to differentiate on type of defects. It will capture image and compare with the dataset in EML model. As more and more photos are added to the dataset, it is able to detect and differentiate more precisely. A hardware module is planned, designed, and contrasted to implement the EML system. The system can be used in various industries that involve welding process.

1.5 Research Outline

The preceding sections briefly summarized the contributions of the thesis. This section outlines the structure of the thesis and summarizes each of the chapters.

Chapter 2 describes the relevant literature and previous work regarding non-conventional welded inspection method. Overview on several non-conventional method and their limitation such as Ultrasonic, Thermography, and Eddy Current method will be explained.

Chapter 3 introduces method or approach taken in order to achieve the three objectives set earlier in Chapter 1. This chapter describes the design for visual detection system for both approaches, software development of EML model using Edge Impulse and hardware implementation using ESP32-CAM module.

Chapter 4 presents the results obtained from the preliminary and experimental work done. Analyses were done on the results. Experimental results obtained validated the preliminary result. Chapter 5 consists of conclusion and suggestion for future improvement.

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