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IoT Based on-the-fly Visual Defect Detection in Railway Tracks

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ABSTRACT:

Railway transportation requires constant inspections and immediate maintenance to ensure public safety. Traditional manual inspections are not only time consuming, and expensive, but the accuracy of defect detection is also subjected to human expertise and efficiency at the time of inspection. Computing and Robotics offer automated IoT based solutions where robots could be deployed on rail-tracks and hard to reach areas, and controlled from control rooms to provide faster inspection. In this paper, a novel automated system based on robotics and visual inspection is proposed. The system provides local image processing while inspecting, cloud storage of information that consist of images of the defected railway tracks only, and robot localization within a range of 3-6 inches. The proposed system utilizes state of the art Machine Learning system and applies it on the images obtained from the tracks in order to classify them as normal or suspicious. Such locations are then marked and more careful inspection can be performed by a dedicated operator with very few locations to inspect (as opposed to the full track).

I.INTRODUCTION

In transport systems, safety and reliability are the main factors that are always questioned, especially in railway transportation systems. Early inspection systems are crucial to maintain safe rail tracks that will ensure safe journeys. Statistics show that 60% of railway accidents are due to derailment, and 90% are due to railway cracks [1]. Railway track cracks could be inspected by human personnel; however, this is not only time consuming, but also the accuracy is subjective since not all cracks are identifiable by naked eyes. As Qatar Rail has launched

the first trains in Qatar recently, it is very important to look for maintenance systems that suits Qatar's climate for railway track inspections. This demand requires inspection systems that will continuously inspect the status of all tracks over Qatar and issue immediate maintenance alerts to avoid accidents. Over the years, machine-driven inspection systems proved to offer a solution for faster inspection and maintenance. Such inspection systems are common in their ability in finding cracks in the rail tracks, as well as the crack's location, which helps the maintenance team to reach and rectify the crack in lesser time. However, solutions vary in terms of being software-based solutions that apply machine vision technologies on recorded videos; or robotic solutions which are automated systems that are deployed on rail tracks and detect cracks using either ultrasonic or IR sensors. Software-based solutions consume time to extract and analyse the images from recorded videos, and robotic-based solutions are limited in their ability in only detecting cracks using sensors without generating results or images. To address these limitations, a novel automated system is proposed in this work that consists of a robot which performs inspection using non-destructive inspection method based on visual inspection with local image processing, cloud storage of information that will consist of images of defected railway tracks only, and robot localization within a range of 3 inches. Local image processing while inspection is a novel inspection technique that will allow for faster inspection in parallel with cloud storage of information, which will only receive images of defected rail tracks.

A. Railway Track Defects:

Railway track defects are divided into two main parts: Internal Defects and Surface Defects [2]. These defects may exist in the head, weld or base section of the track. The most common defects appearing in rail tracks are known as RCF (Rolling Contact Fatigue) which result from the friction in high-speed railways. Another common set of defects is the one resulting from the local climate condition and infrastructure peculiarities. High temperature and humid climate, as in Qatar, causes buckling and heat kinks – also know as sun kinks - in rail tracks. Defects like broken railway tracks or sun-kinks are more crucial than a loose ballast or growth of vegetation.

B. Railway Track Inspection Methods:

Railway track inspection methods are either contact-based which are known as NDT (Non Destructive Testing), or noncontact based methods which is based on analyzing images or videos of the rail-track. Some examples of each type is:

•**Contact-based (NDT): – Ultrasonic Inspection:** this method can detect deep

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internal defects, but fails to detect surface and near surface defects [2], [3], [4], [5]. – MFL (Magnetic Flux Leakage): this technique can detect near surface defects such as RFC, but fails to detect deep internal defects [2]. – Eddy Current Inspection: this technique is based on magnetic fields; therefore, similar to MFL, this technique can detect surface defects, but fails to detect deep internal defects. To overcome this shortage, hybrid solutions combining both ultrasonic and eddy current inspections are available [5]. – Acoustic Emission Inspection: this method is common with steel rail tracks, where it is used to detect crack's growth and accumulation as well as source of crack localization [2].

• **Non-contact-based: – Visual Inspection:** this technique is the most efficient technique used for surface defects detection. It is based on high-speed cameras that capture images of the railway tracks to be processed later based on pattern recognition of the captured images; therefore, it is economical and time saving, but requires higher computational time [2].

II.METHODOLOGY

A) System Architecture

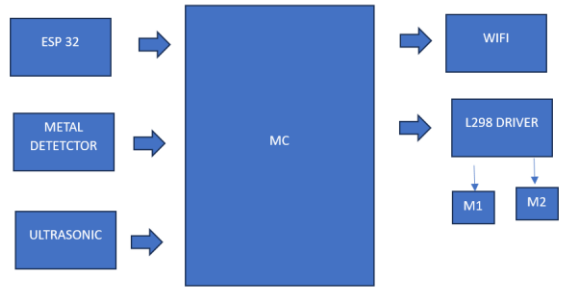

Fig1 .Block Diagram

The system architecture for IoT-based on-the-fly visual defect detection in railway tracks involves the deployment of cameras and sensors on trains or drones to capture high-resolution images and data of the tracks during operation. These images are processed using machine learning and computer vision algorithms to detect visual defects such as cracks, corrosion, or misalignment in real time. The data is transmitted to a cloud platform or local server for further analysis and stored for historical reference. IoT sensors provide additional monitoring, measuring parameters like temperature and vibration, which are crucial for predicting potential track failures. The system triggers immediate alerts to maintenance teams for quick intervention, ensuring track safety and reducing downtime.

B) Proposed Raspberry pi

The Raspberry Pi Pico is an affordable microcontroller board created by the Raspberry Pi Foundation. Unlike full-fledged

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computers, microcontrollers are small and have limited storage and peripheral options, such as the absence of devices like monitors or keyboards. However, the Raspberry Pi Pico is equipped with General Purpose Input/Output (GPIO) pins, similar to the ones found on Raspberry Pi computers, allowing it to connect with and control a variety of electronic devices. Introduced in January 2021, the Raspberry Pi Pico is based on the RP2040 System on Chip (SoC), which is both cost-effective and highly efficient. The RP2040 SoC includes a dual-core ARM Cortex-M0+ processor that is well-known for its low power consumption. The Raspberry Pi Pico is compact, versatile, and performs efficiently, with the RP2040 chip as its core. It can be programmed using either Micro Python or C, providing a flexible platform for users of various experience levels. The board contains several important components, including the RP2040 microcontroller, debugging pins, flash memory, a boot selection button, a programmable LED, a USB port, and a power pin. The RP2040 microcontroller, custom-built by the Raspberry Pi Foundation, is a powerful and affordable processor. It features a dual-core ARM Cortex-M0+ processor running at 133 MHz, 264 KB of internal RAM, and supports up to 16 MB of flash memory. The microcontroller provides a wide range of input/output options, such as I2C, SPI, and GPIO. The Raspberry Pi Pico has 40 pins, including ground (GND) and power (Vcc) pins. These pins are grouped into categories such as Power, Ground, UART, GPIO, PWM, ADC, SPI, I2C, System Control, and Debugging. Unlike the Raspberry Pi computers, the GPIO pins on the Pico can serve multiple functions. For instance, the GP4 and GP5 pins can be set up for digital input/output, or as I2C1 (SDA and SCK) or UART1 (Rx and Tx), though only one function can be used at a time.

C) Design Process

The design of embedded systems follows a methodical, data-driven process that requires precise planning and execution. One of the core elements of this approach is the clear separation between functionality and architecture, which is crucial for moving from the initial concept to the final implementation. In recent years, hardware-software (HW/SW) co-design has gained significant attention, becoming a prominent focus in both academia and industry. This methodology aims to align the development of software and hardware components, addressing the integration challenges that have historically affected the electronics field. For large-scale embedded systems, it is essential to account for concurrency at all levels of abstraction, impacting both hardware and software components. To facilitate this, formal models and transformations are employed throughout the design cycle, ensuring efficient verification and synthesis. Simulation tools are vital for exploring design alternatives and confirming the functional and timing behavior of the system. Hardware can be simulated at different stages, including the electrical circuit, logic gate, or RTL level, often using languages like VHDL. In certain setups, software development tools are integrated with hardware simulators, while in other cases, software runs on the simulated hardware. This method is generally more suited for smaller parts of an embedded system. A practical example of this methodology is the design process using Intel's 80C188EB chip. To reduce complexity and manage the design more effectively, the process is typically divided into four main phases: specification, system synthesis, implementation synthesis, and performance evaluation of the prototype.

APPLICATIONS

Embedded systems are being increasingly incorporated into a wide range of consumer products, such as robotic toys, electronic pets, smart vehicles, and connected home appliances. Leading toy manufacturers have introduced interactive toys designed to create lasting relationships with users, like "Furby" and "AIBO." Furbies mimic a human-like life cycle, starting as babies and growing into adults. "AIBO," which stands for Artificial Intelligence Robot, is an advanced robotic dog with a variety of sophisticated features. In the automotive sector, embedded systems, commonly referred to as telematics systems, are integrated into vehicles to offer services like navigation, security, communication, and entertainment, typically powered by GPS and satellite technology.

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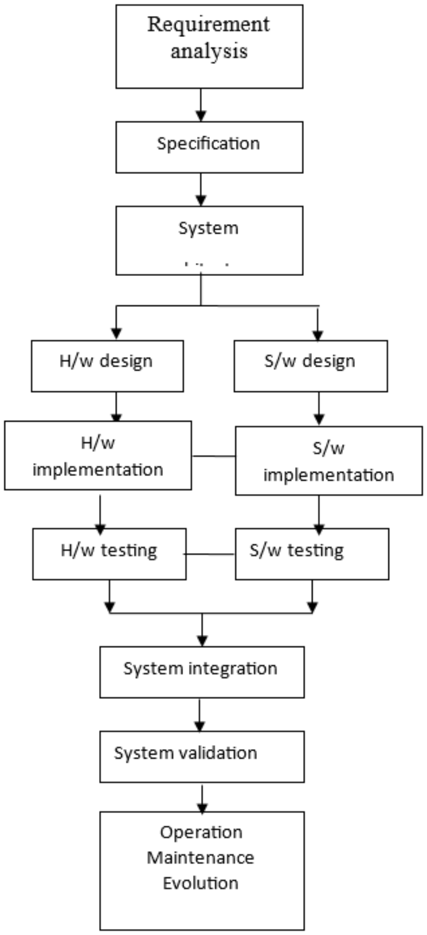

Fig 2. Embedded Development Life Cycle

The use of embedded systems is also expanding in home appliances. For example, LG's DIOS refrigerator allows users to browse the internet, check emails, make video calls, and watch TV. IBM is also developing an air conditioner that can be controlled remotely via the internet. Given the widespread adoption of embedded systems across various industries.

III.CONCLUSION

Rail-tracks early inspection and immediate maintenance are the main major factors to ensure track's safety. Rail-track defects are internal or surface defects, and most commonly results from high-speed friction and climate condition. Available inspection solutions are either contact-based that can be deployed on tracks and controlled from control rooms, or non contact based solutions which is known as machine vision based solutions that can identify and locate cracks by analyzing images of the rail-track. This paper has introduced a novel automated system for rail-track inspection that integrates robotics with visual inspection to detect and locate surface defects. The novelty of thiswork comes from providing an IoT based on-the-fly localdetection while inspection using 2DCNN. While the robot is inspecting, the captured images are sent to the neural network for detection. Once any surface defect is detected, it will be communicated directly to the cloud with the corresponding location for further inspection later. The proposed system has achieved an accuracy rate of 97%. In the future, more sensors will be added to detect internal defects, and the neural network will be trained on GPUs to speed up the training time and enhance the accuracy rate.

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IV.FUTURE SCOPE

The future scope includes integrating AI and deep learning algorithms for more precise defect detection and classification, even in challenging weather conditions or low-light environments. With the adoption of 5G, data transmission speeds can increase, enabling real-time monitoring and analysis across large railway networks. The system could be extended to use autonomous drones or robotic inspection vehicles for more efficient track inspections. Additionally, predictive analytics could be incorporated to forecast potential track issues before they occur, enabling proactive maintenance and reducing disruptions in train services.

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