AL44 - A Deep Learning-Based Robot for Anode Cover Thickness (R-FACT) Measurement in Aluminium Electrolysis Cells

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Abstract

This paper presents a comprehensive study on the design, development, and validation of Robot for Anode Cover Thickness (R-FACT), an innovative automated robot for measuring the anode cover thickness in aluminium electrolysis cells. Addressing the challenges posed by harsh temperatures and elevated magnetic fields in potline environments, R-FACT integrates an Artificial Intelligence (AI)-based deep learning model, Depth Assessment and Recognition of Anode Cover (DARAC), which processes images captured by a dedicated camera to accurately determine the anode cover thickness. The mechanical system design comprises two primary compartments: the base housing power and actuation units and the cooled control compartment housing delicate electronics. A thermoelectric cooling assembly safeguards the electronics, while thermal insulation and magnetic shielding that are strategically placed ensure R-FACT's resilience in demanding environments. The electrical system is meticulously designed to supply adequate power to all components, incorporating safety considerations for charging procedures. The control logic involves a robust combination of three controllers and wireless communication for seamless robot navigation. A fully functional R-FACT prototype was rigorously tested at Emirates Global Aluminium (EGA) facilities, demonstrating notable navigation, effective cooling, and adequate shielding. Crucially, on-site testing of the AI-based measurement model achieved an outstanding accuracy of 97.6 % compared to manual measurements, highlighting R-FACT's potential to automate the anode cover thickness measurement process while significantly enhancing safety for plant operators. The findings of this paper contribute to the ongoing advancements in robotics and AI applications in the industrial sector, paving the way for future research and development.

Keywords: Aluminium electrolysis cells, Anode cover thickness measurement, Artificial intelligence, Deep learning, Robotics.

1. Introduction

The aluminium electrolysis industry heavily relies on the accurate measurement of anode cover thickness for optimising energy consumption, improving process efficiency, and reducing emissions [1]. Traditional measurement methods, such as manual inspections, are labour-intensive, time-consuming, and pose safety risks to workers. This paper presents the design, development, and testing of Robot for Anode Cover Thickness (R-FACT), an automated and Artificial Intelligence-powered system for anode cover thickness measurement. R-FACT integrates an image processing model called Depth Assessment and Recognition of Anode Cover (DARAC) to provide accurate and real-time measurements of anode cover thickness. The successful implementation of R-FACT has the potential to contribute to the enhancement of anode top covering measurement in the aluminium electrolysis industry by improving productivity, reducing costs, and promoting safer working conditions through minimising the need of human intervention in harsh potline environment conditions.

2. Background of Anode Top Covering and its Measurement in Smelters

The process of aluminium electrolysis involves the electrolytic reduction of alumina (Al_2O_3) into aluminium metal in electrolysis cells or pots containing a molten electrolyte mixture mainly composed of cryolite (Na_3AlF_6), aluminium fluoride (AlF_3), calcium fluoride (CaF_2) and alumina. Figure 1 illustrates an electrolysis cell configuration. Carbon anodes are submerged in the electrolyte, and a high electric current is passed through the anode, causing dissolved alumina to be reduced to aluminium at the cathode, which is then collected at the bottom of the cell [2].

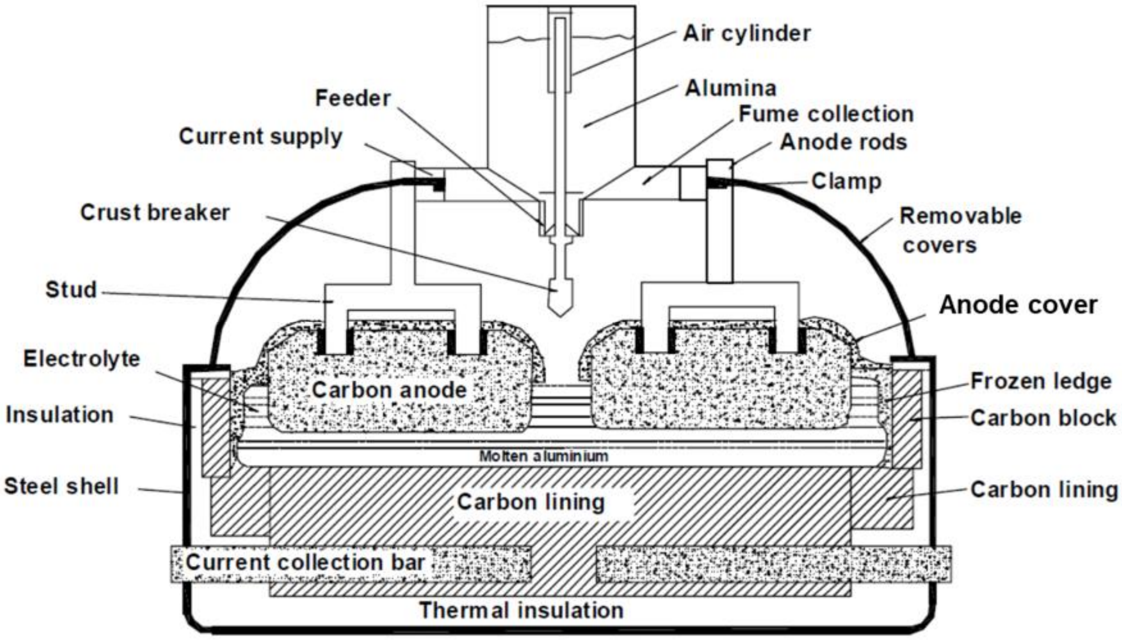

Figure 1. Aluminium electrolysis cell with anode cover, modified from [3].

The thickness of the anode cover, which is a layer of crushed bath and alumina, plays a vital role in the efficiency of the aluminium smelting process [1]. The anode cover layer serves several purposes, including reducing heat loss from the cell, protecting anodes from air oxidation, minimising the release of harmful emissions, and maintaining an optimal temperature within the cell [1]. Accurate measurement of the anode cover thickness is crucial for maintaining optimal cell conditions, which in turn enables timely adjustments to the cover layer, ensuring efficient energy allocation and reducing the environmental impact of the smelting process.

Traditional methods of anode cover thickness measurement involve manual inspections, where operators visually assess the cover layer and use physical tools such as increment-based scale or rods to determine its thickness. These methods present several limitations:

- Labour-intensive: Manual inspections require significant human effort and are time-consuming, leading to reduced operational efficiency.

- Inconsistency: Human assessments in their nature are subjective and prone to errors, resulting in inconsistent and potentially inaccurate measurements.
- Safety risks: Manual inspections expose technicians to hazardous conditions, such as high temperatures, reaching up to 90 °C in the potline environment, high magnetic fields up to 50 mT, and low air quality caused by dust, posing significant safety risks.
- Limited frequency: Due to the time-consuming nature of manual inspections, they are performed at a relatively low frequency, which may result in suboptimal anode cover thickness and increased energy consumption.

These limitations emphasise the need for an automated, accurate, and safe measurement system capable of providing real-time data on anode cover thickness, enabling operators to maintain optimal cell conditions and contribute to the overall efficiency of the aluminium smelting process. To address this need, an appropriate system should have the following features:

- Automation: The system should measure anode cover thickness autonomously, minimising human intervention and increasing operational efficiency.
- Accuracy: High accuracy in measurements is essential for maintaining optimal cell conditions and reducing energy consumption.
- Real-time data: The system should provide real-time information on anode cover thickness, enabling timely adjustments and ensuring optimal cell performance.
- Safety: By eliminating the need for manual inspections, the system should significantly reduce safety risks associated with hazardous working conditions.
- Integration: The system should be easily integrated with existing infrastructure and processes, facilitating seamless implementation and minimal disruption to operations.

To meet these requirements, this paper introduces the Robot for Anode Cover Thickness (R-FACT) Measurement System, developed in collaboration with Emirates Global Aluminium (EGA). The R-FACT system leverages advanced robotics and artificial intelligence (AI) technologies to provide a reliable, accurate, and safe solution for anode cover thickness measurement. This robot won the fifth edition of Al Robot, EGA's competition that challenges students from UAE universities and higher education institutions to design and construct prototype industrial robots for deployment at EGA's aluminium smelters [4].

The objective of this paper is to provide a comprehensive technical overview of the R-FACT system, detailing its design, development, and testing. The paper delves into the technical aspects of the Artificial Intelligence-powered measurement model, namely the Depth Assessment and Recognition of Anode Cover (DARAC) model, the mechanical system design, and the supporting electrical, cooling, and control systems. Furthermore, the testing results are analysed and the advantages of R-FACT over existing measurement methods are discussed. The paper also highlights the significance of R-FACT for the aluminium industry and potential areas for further improvements and applications. By presenting a thorough investigation of the R-FACT system, this paper aims to demonstrate its potential to address the limitations of current anode cover thickness measurement practices and contribute to a safer and more efficient aluminium smelting process.

3. R-FACT Mechanical System Development

This section presents the mechanical design approach used for a specialised four-wheel skid steering drive robot, developed to operate in high temperature and high magnetic field environments, particularly in aluminium smelter pot lines. The mechanical system is designed with a focus on identifying key design elements essential to the robot's success in order to fulfill the particular demands of this harsh environment. This section covers important design elements like the type of actuators, the nature of the thermal system chosen to cool the electronic compartment, the magnetic insulation, thermal insulation, and more. The end product is a highly specialised robot that can work well in strong magnetic fields and temperatures.

The development of the R-FACT robot for aluminium smelter pot lines requires careful consideration of various design constraints. These constraints include the maximum allowed width of the robot to pass through the tight entrance of the pot lines, the need for the robot to be lightweight yet robust enough to withstand the harsh operating environment, and the ability to operate in environments with high levels of dust. Figure 2 shows the tight entrance constraint. Additionally, the robot has to be able to operate in high temperatures up to 90 °C and a magnetic field of 50 mT, which requires the incorporation of thermal insulation and magnetic shielding into the design. Ferromagnetic materials like steel are not suitable due to their magnetic interference and potential for degradation and damage over time. Therefore, a higher grade of aluminium alloy is chosen for the chassis of the robot. These constraints require to balance the weight of the robot with its strength and durability, and to carefully consider how the dust will impact the system's performance.

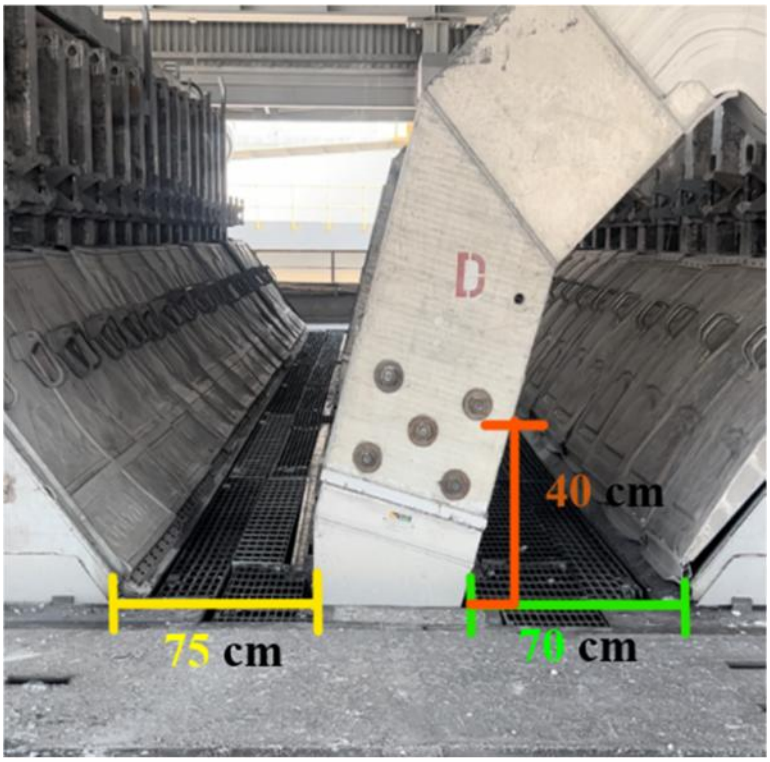

Figure 2. Dimensions constraints for access between two cells.

The mechanical system of R-FACT is divided into four parts: the robot chassis, battery and motor brackets placement, wheel-shaft-cup assembly, and cooled control compartment. To provide a detailed view at the R-FACT robot's mechanical system, Figure 3 is included to show a semi-transparent view of the robot showing the placement of all components. This figure provides a clearer understanding of the robot's internal components, their placement, and the layout and distribution of the various parts within the chassis. Further explanation of the individual components and their functions will be provided in this section, building upon the insights gained from these figures.

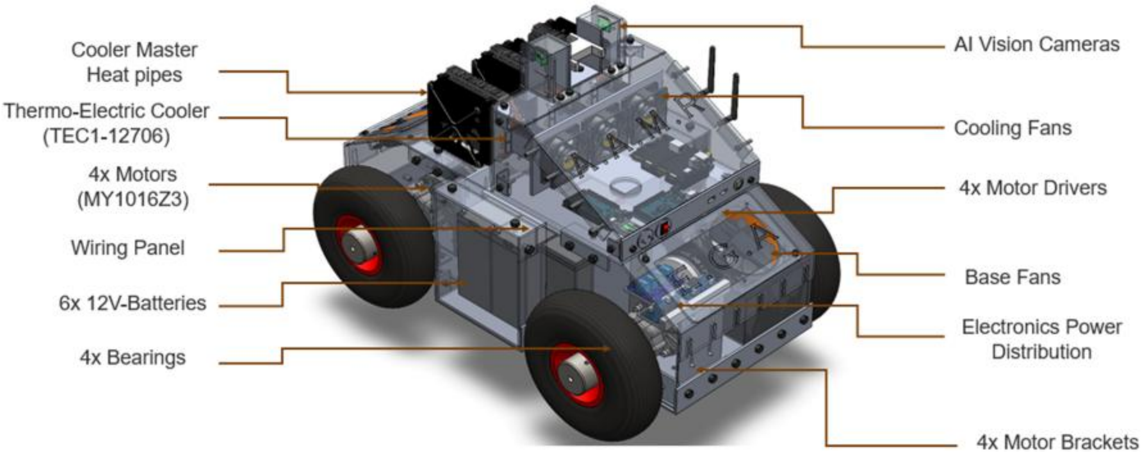

Figure 3. R-FACT 3D transparent view.

The R-FACT robot's chassis is an essential component that provides support and protection for its main electronic systems and components. The design of the chassis considered several factors, such as material, shape, and size, and incorporated a flat metal sheet as the base shown in Figure 4 allowing for easy modifications during the design process. Structural supports and features such as holes and slots were added to the base for added stability.

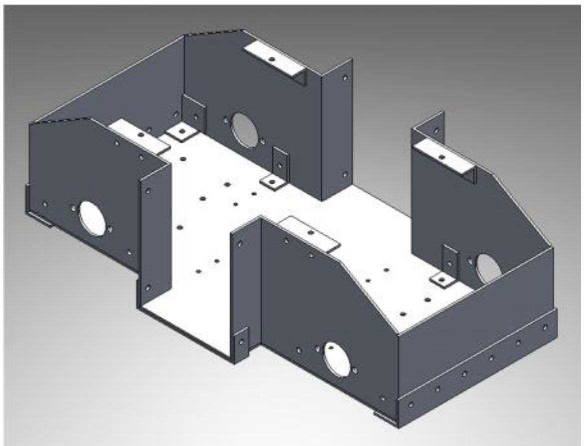

Figure 4. R-FACT base chassis.

The walls of the chassis were specifically designed to incorporate bearings to prevent any vertical loading on the motor shaft. By distributing the load acting on the bearing to the base through the walls, the chassis is able to effectively handle the various forces and stresses experienced by the robot during operation, ensuring that it remains stable and durable throughout its lifespan, which helped protect the motor from excessive stress and strain that could lead to premature wear and tear or failure. Custom designed 90-degree brackets were utilised to connect and fix the walls and upper compartment elements to the base. These brackets were made using the same material as the chassis and were strategically placed at various points along the chassis to provide stability and distribute the load evenly across the chassis. They also played a role in minimising any unnecessary movement or vibrations that could affect the robot's performance.

350 W motors were selected for the robot due to the challenging conditions of operating in aluminium smelter pot lines. The motors were left-oriented only, and the alignment of the shaft was considered when designing and placing the motor brackets. Figure 5 shows the motor brackets. Due to the clearance needed from the base to the ground, it was challenging to place the motor in its original position. To solve this issue, the motor was oriented to minimise the distance

between the shaft and the base. The R-FACT robot's battery pack comprises almost 90 % of its total weight, divided into two clusters. The first cluster consists of four tightly-packed batteries positioned at the center of the base, while the other cluster contains a single battery symmetrically placed on both ends of the first cluster, as shown in Figure 6. To maintain stability and prevent undesired movement, a single u-shaped connector is designed to fix the batteries to the base. A separate battery is dedicated to the measurement system, fixed in place through a tight fit using a 3D-printed designed raiser.

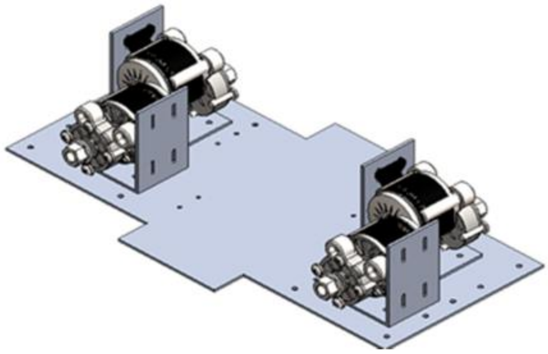

Figure 5. Motor brackets.

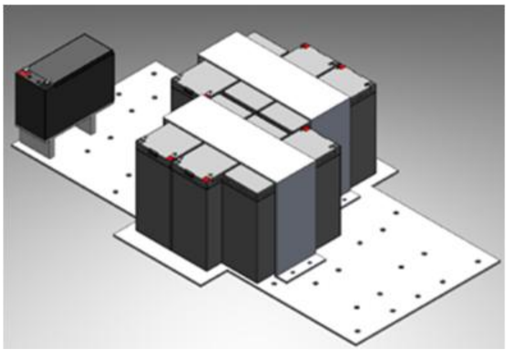

Figure 6. Design of battery brackets.

The cooled control compartment in Figure 7 was designed with accessibility, thermal insulation, magnetic shielding, and Peltier cooling assembly in mind. Heat pipes and fans radiate heat from the hot side of the TEC module, while fins distribute coldness on the cold side, and fans circulate cold air into the compartment. The compartment houses all the controllers and Nvidia Computer Board, making the design complex. The Peltier cooling assembly ensures that the sensitive electronics in the control compartment remain functional in high-temperature and high-humidity conditions.

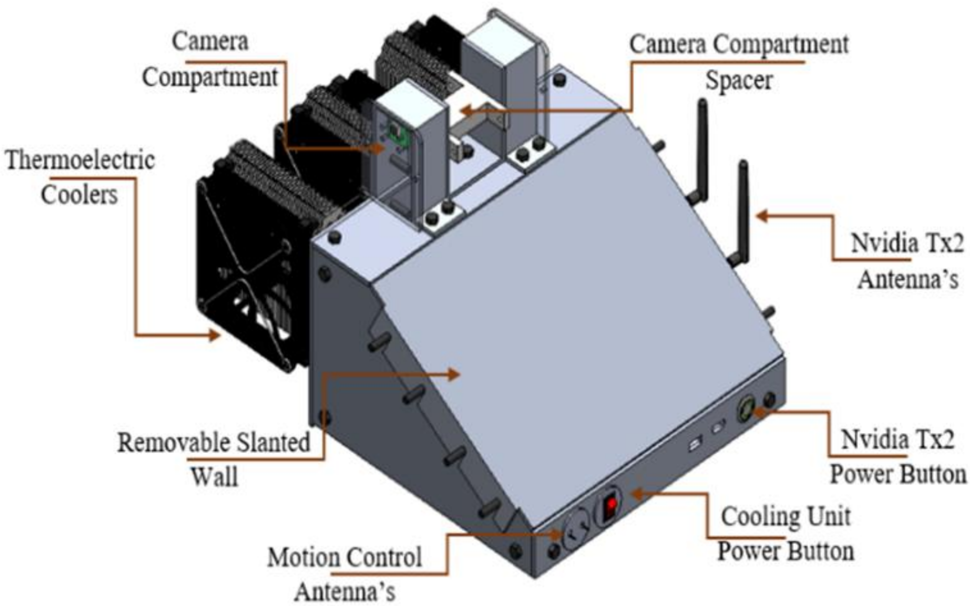

Figure 7. Cooled control compartment.

Figure 8 shows the layout arrangement of the controllers and the NVIDIA computer board. The placement of controllers and the NVIDIA computer board is optimised to minimise wiring issues and tangles. A layout of arrangement is generated, and the Peltier cooling assembly, containing three ThermoElectric Coolers (TEC) modules, three heat pipes, three fins, four hot side fans, and three cold side fans, is designed to effectively cool the sensitive electronics. Prebuilt connectors are used to optimise the cooling assembly, which are specifically designed to work for CPUs and fit into computer motherboards easily, ensuring effective cooling of the compartment's components.

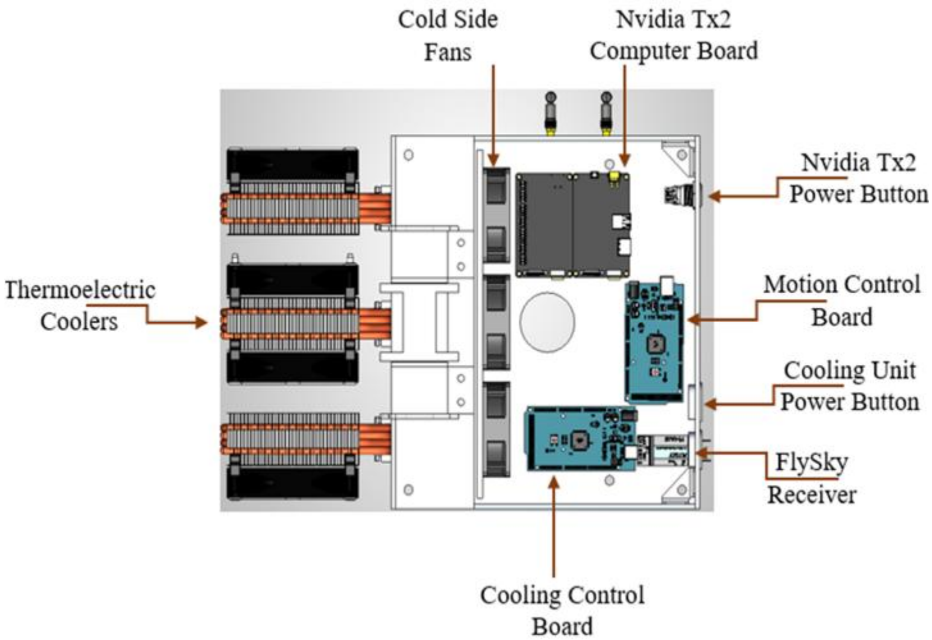

Figure 8. Controllers' layout arrangement.

The robot chassis material selection was influenced by the need to avoid interference with the smelting process, leading to the selection of non-ferromagnetic aluminium alloy 5052 due to its high ductility, machinability, point of fracture, and lightweight nature. The chassis is designed with a rectangular base with dimensions of 75 x 52.25 cm to enhance stability and structural rigidity compared to other shapes. The uniform weight distribution of a rectangular base makes it less likely to topple over and more resistant to torsion and bending moments, a critical factor for a robot operating in a harsh industrial environment like a smelter. Additionally, the rectangular shape provides more efficient use of space within the chassis, making it easier to mount various components and accessories such as motors, sensors, and control units. Therefore, the rectangular shape is the most suitable base for the robot chassis due to its superior stability, efficient use of space, and ability to distribute forces evenly across its surface, making it versatile and adaptable to changing operational requirements.

4. Artificial Intelligence (AI) Measurement System Development

The core constituent of the R-FACT system is an Artificial Intelligence-based measurement model called DARAC, which stands for Depth Assessment and Recognition of Anode Cover. The primary purpose of DARAC is to accurately measure the thickness of the anode cover by analysing images captured by the system's cameras. This section discusses the development and training of the DARAC model, as well as the methodology used for its validation. The DARAC model is based on deep learning techniques, particularly an integration of Convolutional Neural Networks (CNNs) and Artificial Neural Networks (ANNs), which as networks have a demonstrated remarkable success in computer vision tasks [5]. The model is designed to analyse images of anode assemblies and estimate their thickness by detecting key points on the anode surfaces and consecutively employ an AI measurement algorithm. This section provides a detailed description of the model development and training process.

Supervised learning constitutes the main training methodology for the DARAC model development. Data preparation plays a crucial role in the development of the DARAC model. A diverse dataset of images featuring various anode assemblies was gathered to train and validate the model. The dataset included images captured from different angles and lighting conditions configurations to ensure robustness and generalisability. During the preprocessing stage, the images were resized to a consistent resolution, and additional data augmentation techniques, such as rotation, flipping, and zooming, were applied to increase the dataset's size and diversity, further improving the model's performance on unseen data.

The DARAC detection model employs a Convolutional Neural Network (CNN) architecture, consisting of a series of convolutional layers, activation functions, and pooling layers, followed by fully connected layers for final output prediction, such as shown by Figure 9. The convolutional layers are designed to detect local features within the input images, while the pooling layers reduce the spatial dimensions, providing translation invariance and reducing the number of parameters [6]. The fully connected layers produce the final output, which consists of key point coordinates on the anode assembly surfaces.

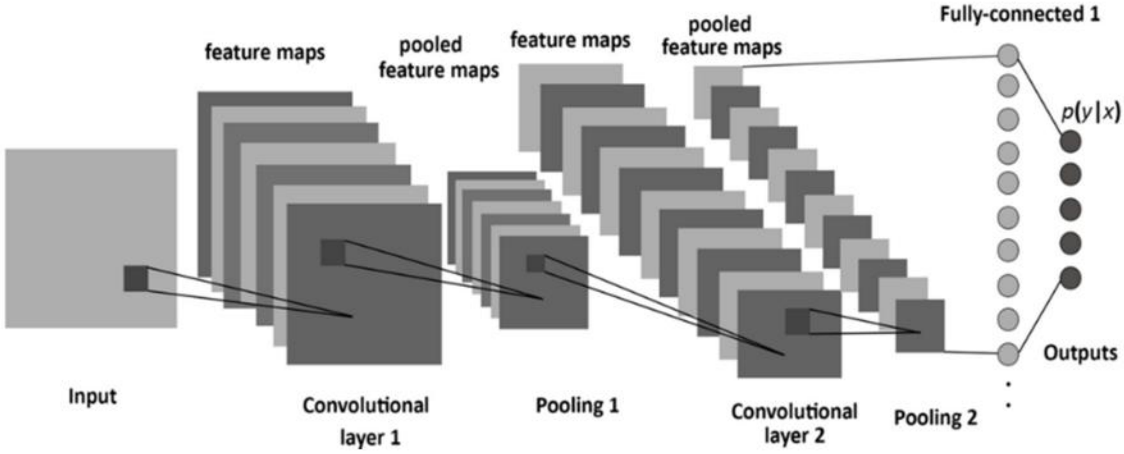

Figure 9. CNN architecture [6].

The training process involved minimising the mean squared error (MSE) loss function, which measures the difference between the predicted key points and the ground truth labels. The model was trained for a predetermined number of epochs, with early stopping implemented to prevent overfitting. The model's performance was evaluated on a validation set, which was not used during training, to assess its generalisation capabilities. To accelerate the training process and improve the model's performance, transfer learning is employed. A pre-trained CNN model, ResNet50, is utilised as a feature extractor. The pre-trained model's weights are pre-initialised with the weights learned from a large-scale dataset which contains millions of images and thousands of object classes [7]. In DARAC development, the final layers of the pre-trained ResNet50 model are replaced with custom layers designed for the anode assembly thickness estimation task. Fine-tuning was performed using a smaller learning rate than the initial training to prevent the loss of valuable information gained from the pre-trained model.

In addition to the CNN architecture, the DARAC model also incorporates an Artificial Neural Network (ANN) to refine the thickness measurement. While the CNN focuses on detecting key points on the anode assembly surfaces, the ANN serves as a post-processing step, estimating the thickness based on the key points identified by the CNN. The ANN is composed of multiple layers of interconnected neurons, with each neuron processing input data through a series of weighted connections, activation functions, and biases. The ANN is designed to learn the underlying relationships between the key points detected by the CNN and the corresponding thickness measurements, providing a more accurate and robust estimation.

After the individual training of both the CNN and ANN components, the two models were integrated into a single end-to-end pipeline. The output of the CNN (i.e., the key point coordinates) served as the input to the ANN, which then estimated the thickness of the anode assembly based on the key points. The DARAC model's performance was evaluated using multiple metrics, including target value distribution, loss per epoch, pair plot analysis, and loss distribution. These metrics were chosen to provide a comprehensive understanding of the model's accuracy and reliability in estimating anode assembly thickness. Monitoring the loss per epoch is crucial for preventing overfitting and underfitting, which can adversely impact the model's performance on unseen data. Pair plot analysis allowed for the identification of linear or nonlinear relationships, clusters, or outliers, indicating that the model can identify and learn the underlying patterns and relationships between the features.

To provide an objective assessment of the model's performance, a separate test set of images was utilised, which had not been included in the training or validation procedures. This test set consisted of a varied collection of anode assembly images, captured under various conditions and configurations. The DARAC model was then applied to this test set, and performance metrics were computed based on the predicted key points and the ground truth labels. The evaluation and performance analysis of the DARAC model revealed several key findings. The model's ability to capture the underlying data patterns accurately, fit the training data, and avoid overfitting or underfitting was confirmed. Relationships between different features and their impact on the model's performance were identified through pair plot analysis. Loss distribution analysis allowed for a deeper understanding of the model's performance across various error magnitudes. Overall, the results of this evaluation and analysis provided confidence in the effectiveness of the DARAC model and highlighted its suitability for integration with the R-FACT system and implementation in real-world applications.

5. Electrical and Electronic System Design

The electrical and electronic system of Robot for Anode Cover Thickness (R-FACT) includes all electrical and electronic components that serve as power supply, actuators, controllers, sensors, and other functions. Seven Lead-Acid batteries supply the robot with the necessary power while ensuring adequate time of operation before charging. Six of the batteries are 12 volt and 22 ampere-hour cyclic application batteries. While the seventh battery is 12 volt and 7 ampere-hour cyclic application battery. The battery configuration is split into three subsystems, actuator power supply, cooled control compartment power supply, and Depth Assessment and Recognition of Anode Cover (DARAC) power supply. The actuator power supply involves four of the 12-volt, 22 ampere-hour batteries, where two pairs are connected in series for an output of each pair of 24-volt, 22 ampere-hour. Each pair powers two 24-volt actuators. The cooled control compartment power supply involves two of the 12-volt, 22 ampere-hour batteries, which are connected in parallel for an output of 12-volt and 44 ampere-hour. The cooled control compartment power supply provides power to the cooling system and all electronics, where a dc-dc step down converter is utilised to step down the voltage reaching the electronics to 7-volt. Finally, the DARAC power supply involves the seventh 12-volt, 7 ampere-hour battery which first passes through another dc-dc step down converter to regulate power reaching the electronics and hardware responsible for performing DARAC. Moreover, charging is split into 24-volt charging and 12-volt charging, where the actuator power supply is charged at 24-volt, and the cooled control compartment and DARAC power supply are charged together at 12-volt.

The actuators of R-FACT include four motors. Each motor is a 24-volt, 350 W DC motor, including a built-in 9.78:1 gear ratio that outputs at the rated power of 350 W, 300 RPM and 11.1 N-m. The reason behind the selection of such motors includes high starting torque and efficiency. Nonetheless, the motors will not run at their rated power but will rather be run at a lower power using pulse width modulation (PWM). The motors will run at 10-30 % duty cycle, depending on whether the robot is translating or steering, which would decrease the power consumption of each motor to around 105 W. Based on the actuators power supply and the motor power consumption, a maximum continuous operation time of 1.5 hours can be supplied to each motor before charging. Each motor is connected to a motor driver to control the direction and power reaching them. The motor driver has built-in over-current, over-temperature, and under-voltage protection features to ensure the safe operation of the motor and driver.

The robot includes three controllers involving Arduino Mega, Arduino Uno, and Nvidia Jetson TX2 NX. The Arduino Mega is the robot base controller involving motion control and wireless control. The Arduino Uno is the cooled control compartment controller, further utilising a four-channel relay to control the cooling system and provide a temperature monitoring system involving two DS18B20 temperature sensors, where one tracks the base temperature, and the other tracks the cooled control compartment temperature. The Nvidia Jetson TX2 NX computer module provides high-performance and efficient artificial intelligence capabilities, having the ability to run multiple deep neural networks and other artificial intelligence algorithms in parallel. This contributes to performing DARAC efficiently, which is the main function of it in the robot.

6. Cooling System Design

The Thermoelectric Modules are considered the cooling units for the enclosure. Thermoelectric cooling is a technology that utilises the Peltier effect to generate a temperature differential across a semiconductor material. The Peltier effect is a phenomenon where an electric current is passed through two dissimilar conductors, creating a temperature difference between them. This temperature difference can be used to transfer heat from one side of the semiconductor to the other, resulting in cooling or heating of the material.

Thermoelectric Modules 12706, a Copper Heat Sink and a Cooler Master Hyper 212 EVO V2 Heat Pipe are used to allow for a heat transfer from the enclosure to the surroundings. By placing a thermoelectric cooler in between a heat pipe assembly and a heat sink, it can create a temperature gradient that allows for efficient heat transfer. The heat pipe assembly and heat sink provide a pathway for the heat to be dissipated away from the electronics, while the thermoelectric cooler actively removes heat from the enclosure. The number of Peltier Modules, or Thermoelectric Modules decides the cooling load provided, or the capacity of the cooling unit to remove heat trapped in the enclosure. The number of Peltier elements is obtained through a thermal analysis phase of the electronics compartment. To calculate the heat load generated which corresponds to the cooling load that should be provided by the cooling units, the following formula is used:

$$Q = U \times A \times \Delta T \tag{1}$$

Where:

U	Thermal transmittance in W/m^2
K and A	Surface area of the sides in m^2, and
ΔT	Temperature difference between the enclosure or the desired temperature inside the enclosure and the surrounding environment in K.

To calculate the U-value:

$$U = \frac{1}{R_{total}} \tag{2}$$

where R_{total} is:

$$R_{total} = R_{AL} + R_{INS}\ ;\ R = \frac{l}{k} = \frac{Thickness}{Thermal\ condctivity} \tag{3}$$

In Equation (2), R_{total} is the total resistance which includes the resistance caused by the aluminium sheet (AL) and the Insulation layer (INS). The transmission heat load, or the load trapped form the environment outside, of the enclosure is calculated to be 38.8 W. this is calculated using Equation (1). While the active heat load consumed by the electronics in the enclosure is considered to be 15 W, giving a total heat load of 53.8 W multiplied by a factor of safety of 2 to give a 107.5 W of heat load, which is the amount the heat needed to be removed from the enclosure, or so-called cooling load. Moreover, one Peltier Module provides a maximum of 60 W of cooling, taking into consideration the thermal resistance created by the heat sink attached and air circulation to have the cold air of the 60 W of cooling to reach the electronics, and eventually the whole enclosure, 60 W will not be fully used to transfer heat from the enclosure to the ambient also since the Peltier module will not always provide its maximum cooling load. Therefore, three Peltier Modules ensure a better functionality of the cooling system.

7. System Control Logic Development

Aside from AI-DARAC system, the other main systems of the robot, namely the motion, cooling, and temperature measurement systems, are controlled using two Arduino microcontrollers. Figure 10 provides a flowchart that explains the part of the code responsible for the control logic of the robot mobility, utilising an Arduino Mega board. The code starts with the initialisation of wireless communication functions and serial communication before entering an infinite loop. In the loop, there are five conditions (if statements) for different robot maneuvers, including moving forward, backward, spinning clockwise, spinning counter-clockwise, and standing-by. The right joystick (RJS) is the dominant joystick, meaning it takes precedence over the left joystick (LJS) if both are moved. A safety measure of a two-second delay is applied after a motion command is given to prevent accidental movements by the operator, especially in such a hazardous operation environment. The flowchart ends with a return block. The triangle block A indicates the connection to another part of the code responsible for the wireless communication functions, discussed briefly in the following paragraph.

The code defines two wireless communication functions. The first one is Read_Int_Ch, which reads the channels of the remote controller and returns an integer between 0 and 1023, allowing for the mapping of the joysticks movement to values between 0 and 1023. The second function, Read_Bool_Ch, returns a Boolean value of 1 or 0 depending on whether the Power Mode Switch or the Cooling Switch on the remote-controller is ON or OFF. When the Power Mode Switch is ON, more power is delivered to the motors, which is useful for maneuvering on rough or inclined terrain. Depending on the state of the Cooling System Switch (i.e., whether ON or OFF), a Cooling System Variable is set to 1 or 0, respectively, which is responsible for the wireless activation/deactivation of the cooling system.

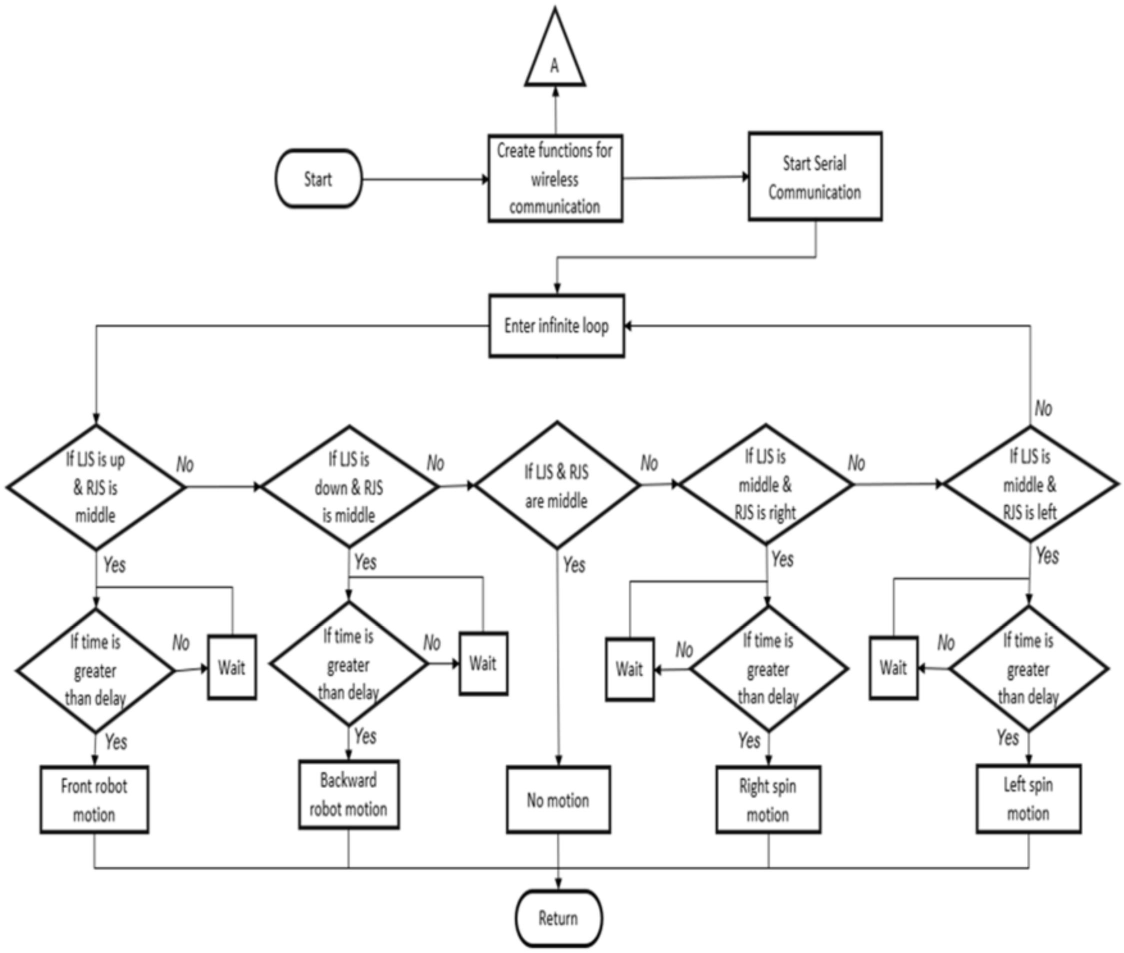

Figure 10. Control logic flowchart of the robot mobility.

On the other hand, the mechanical activation/deactivation of the cooling system and the temperature monitoring system are controlled using an Arduino UNO board. The code starts with initialising serial communication and then enters an infinite loop. A Mechanical Switch State Variable is declared in the code, which stores the state of the Mechanical Cooling Switch. If the state of this switch is ON, the cooling system is turned ON. The Cooling System Variable (which is previously discussed and declared in the Arduino Mega Code) is read, and if its value is 1, another variable, namely Wireless Control Variable, is set to 1, and the cooling system is activated. This communication between the Arduino Mega and Arduino UNO boards is made possible by connecting one pin on the Arduino UNO (from which the Cooling System Variable stores values) to another pin on the Arduino Mega (from which the Wireless Control Variable stores values) via a jumper wire. Moreover, the Mechanical Cooling Switch is dominant, meaning that if it is ON, the cooling system will be activated regardless of the state of the Wireless Cooling Switch. This also means that, in order to wirelessly control the cooling system, the Mechanical Cooling Switch state should be OFF. Furthermore, two temperature sensors are present in the robot, and two temperature variables have been declared to store their values. The temperature variables are read in the code, and their values are outputted to the serial monitor to monitor the temperature in the Cooled Control Compartment and the Base. The Base houses the electrical components, and the Cooled Control Compartment contains the electronic components, except for the motor drivers, which are placed in the Base instead.

8. System Testing and Results

8.1 Lab-Controlled Testing

After developing the Depth Assessment and Recognition of Anode Cover (DARAC) measurement system and training the AI model with data, it is essential to test its effectiveness on a dataset that it has not encountered before. The test aims to evaluate the yoke detection model's effectiveness by examining the reference points that the model has established for new data and to compare the measurement value with actual measured values, overall creating a simulated real-life scenario. Figure 11 illustrates the test results. As shown in Figure 11, the reference points established by the model are relatively accurate and effectively capture the yoke. Moreover, the measurements in millimeters for the left and right sides are displayed on the top left and top right, respectively, of the figure.

The measurement for the left side is 175 mm, while the measurement for the right side is 160 mm. The actual values for anode top cover thickness were 170 mm for the left side and 165 mm for the right side. The error percentage for the left-side measurement is 2.94 %, while the error percentage for the right-side measurement is 3.03 %. The error percentage falls within an acceptable range and meets the design objective. The next section provides details on on-site testing of the AI measurement system, or DARAC.

Figure 11. Measurement system simulation result.

To test the cooling system behavior, at test was performed in the lab under controlled parameters. The assembly of the Thermoelectric (TEC) module is brought and attached in a small enclosed environment that has similar dimensions to the electronics enclosure. Then after starting the cooling process, a constant heat flux is projected to the hot side of the assembly, the temperature is observed and recorded on a fixed time interval of 60 seconds. The goal of this experiment is to analyse and record the time it takes to stabilise and to reach the maximum temperature difference. Note that the enclosure is not insulated in this experiment just to observe the effect of hot ambient directly to the thermoelectric module behavior. The temperature difference in this experiment between the hot and cold side from 1 to 10 minutes is calculated to be 12.1 °C. This experiment did not carry on any thermal insulation. The temperature values were recorded for 20 minutes when cooling started along with a constant heat flux applied to the hot side along with a graphed representation of the results in Figure 12.

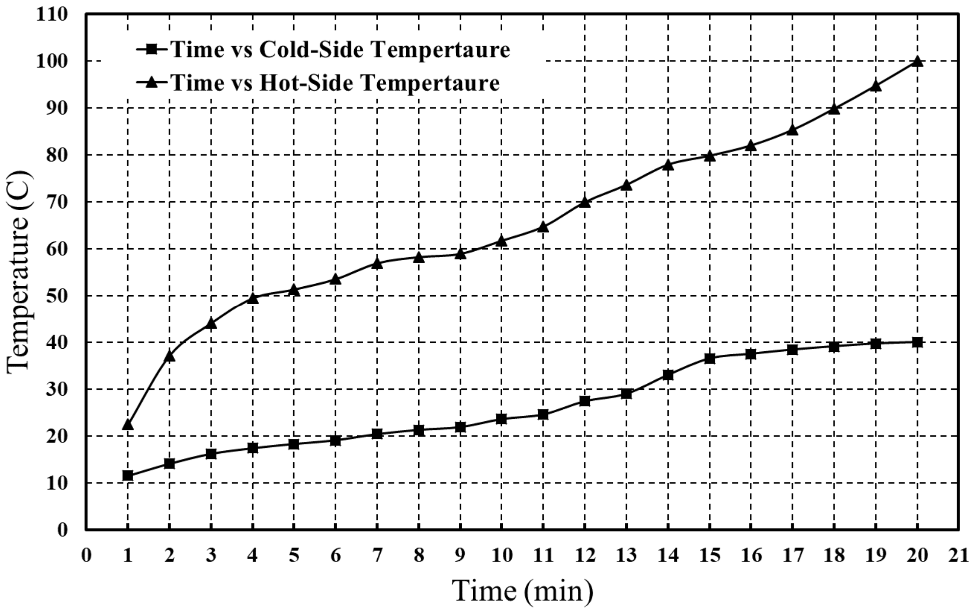

Figure 12. Cooling system experiment.

8.2 On-Site Testing

As mentioned in the previous section, the in-lab testing of the DARAC Artificial-Intelligence measurement model, dependent on a dataset that the model had not seen during training, provided an upper error of 3.03 % at the final stage of development. During the on-site testing at Emirates Global Aluminium (EGA) premises, DARAC was employed to measure the anode cover thickness of various electrolysis cells residing in the same potline in the company's Jabal Ali facility, in a testing collaboration that mainly aimed to evaluate and provide a demonstration of the system's effectiveness and robustness. The on-site measurement trials proved to be a success, and the AI-based measurements were then compared with manual measurements taken by plant operators. The comparison revealed a 97.6 % accuracy rate for the Artificial Intelligence model, further confirming its reliability and effectiveness in a real-world setting.

The thermoelectric cooling system was also tested under controlled parameters at EGA premises. In the lab, a constant heat flux was projected to the hot side of the assembly, with temperature observations recorded at fixed time intervals of 60 seconds. The temperature difference between the hot and cold sides reached 12.1 °C in the lab experiment, while at the EGA premises, where thermal insulation was applied, the temperature difference was 7.6 °C. These results show that the cooling system effectively protects the electronics within the robot, ensuring its functionality in the high-temperature environment of aluminium smelters.

9. Discussion and Potential for Improvement

This section emphasises the significance of Robot for Anode Cover Thickness (R-FACT) for the aluminium industry, the advantages it provides over conventional methods of measurement, and the potential for further improvement and work on the system. R-FACT provides a solution for automating the process of measuring the anode top cover thickness in aluminium smelters. The robot involves a robust design that can withstand the harsh environmental factors in the aluminium pot lines that R-FACT is designed for. This aids in limiting employee exposure to the harsh environment during the measurement. The development and testing of the Depth Assessment and Recognition of Anode Cover (DARAC) model for the measurement of anode top covers in aluminium smelters has showcased potential for improving efficiency and precision in the industry, with an accuracy of 97.6 % relative to the conventional manual measurement. The use of deep learning models, namely the detection and measurement models, has provided an innovative solution to a long-standing challenge in the industry. To surpass the limitations of traditional measurement methods, the DARAC model utilises the Keypoint R-CNN (Region-based Convolutional Neural Network) architecture in the detection model. This advanced technique facilitates the accurate identification and extraction of the region of interest (ROI) from an image that contains the anode top cover. The ROI is then fed to the measurement model, which employs an artificial neural network (ANN) to predict the thickness of the anode top cover. The use of deep learning models has emerged as a breakthrough for the industry, offering an efficient and precise approach to anode top cover measurement. The capability to accurately identify the ROI ensures that the measurement model can provide reliable predictions for the thickness of the anode top cover. This is a crucial element of the overall process, as the precision of the measurement is vital to the performance and productivity of the aluminium smelter.

The potential for the DARAC model to reduce human error in the measurement of anode top covers cannot be overstated. Traditional measurement methods involve manual measurement by technicians, which is often time-consuming, error-prone, and can lead to inconsistent results. The use of the DARAC model in this context can significantly improve the accuracy of the measurement and reduce the risk of errors. R-FACT physical design has room for optimisation in terms of reducing weight, enhancing steering, and DARAC model improvement. The robot weight can be reduced through a careful study of safe integration of lithium-ion batteries instead of the lead-acid batteries into the system, which are generally a lightweight option whilst providing the required power supply. The steering may be enhanced by conducting an experiment of carefully increasing the pulse width modulation signal duty cycle to provide the appropriate power for steering within the pot line, which was previously overengineered to steer on asphalt. The DARAC model's accuracy was assessed using quantitative metrics, such as target distribution, loss per epoch, pair plots, and loss histogram. The model displayed promising results in accurately capturing the target distribution and fitting the data, indicating potential for more efficient and accurate measurements. However, analysis of pair plots and loss histogram identified areas for improvement, guiding further research and development. Overall, the assessment provides valuable insights for the DARAC model's implementation in real-world applications.

10. Conclusions

This paper explores the design, fabrication, and testing of R-FACT, a robot that measures the anode covering crust level of aluminium smelting cells at EGA through an AI-based deep learning model. The scope of the project includes developing the DARAC model, designing the R-FACT mechanical, electrical, and cooling systems, integrating wireless communication, producing a prototype, managing the project budget, and documenting the process. The developed model was tested in simulations and on-field with the physical prototype, providing accurate measurements of anode covering crust with a real-time accuracy of 97.6 %. Therefore, it can be inferred that R-FACT can automate the measurement of anode cover thickness while maintaining accuracy and effectiveness, limiting human intervention in harsh conditions, and ensuring operator safety. As a closing note, R-FACT can provide substantial value to the plant and is a promising adaptation in the aluminium industry.

11. References

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