The University Of Sheffield.

Aerospace Engineering

Interim Report Assignment Cover Sheet

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Assignment Title:	Machine Learning methods for the classification of microstructural features in materials for aerospace engineering applications		
Supervisor:	Dr. M. Thomas		
Submission Date:	14th December 2023		

Student Declaration

I confirm that the work I have submitted is my own original work and that I have made appropriate references to any sources used.

I agree to any submitted materials being used by the Department and/or University to detect and take action on any unfair means.

I confirm that the printed version of this assessment and any electronic copy I am required to submit to TurnItIn are identical.

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3. A formal reprimand (warning) being placed on my student record at Departmental and/or University level which may be taken into account whenever references are written.
4. Reporting of the incident to the University Disciplinary Committee.
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Signature:	EEdmunds
Date:	14th December 2023

BEng Aerospace Individual Investigative Project

Interim Report

Machine Learning methods for the classification of microstructural features in materials for aerospace engineering applications

Ethan L. Edmunds

Date: 14th December 2023

Supervisor: Dr. M. Thomas

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Introduction/Background

In the field of aerospace engineering, the selection of appropriate engineering alloys plays a major role in determining the performance and longevity of aircraft components. These alloys are chosen based on specific physical properties, including structural integrity, low density, and heat transfer coefficients. However, an inherent challenge lies in the potential presence of defects such as cracks, pores, and fusion defects, which can significantly compromise the performance and service life of these materials [1].

Amidst these challenges, machine learning emerges as a technology that has unlocked numerous opportunities across diverse engineering disciplines, with Materials Science and Engineering being no exception. A growing body of research has showcased the capabilities of machine learning in supporting materials science investigations and engineering applications [1-3]. Notably, both supervised and unsupervised machine learning methods have demonstrated their prowess in accurately predicting defects in aerospace materials.

Research conducted by Aziz et al. shows the capabilities of machine learning in defect prediction. Their research highlights the effectiveness of supervised methods like the KNN classification algorithm and unsupervised methods such as decision trees in accurately classifying defects in additively manufactured nickel alloys [1]. This underscores the potential of machine learning as a powerful tool for enhancing our understanding of material behaviour and addressing critical challenges in the aerospace industry. The hope for this project is to show the capabilities of machine learning in classifying defects in abradable coatings, that are used in seal coating systems for gas turbines and gas compressor systems, as currently employed image segmentation models struggle to classify defects within the samples [4].

Aims and Objectives

ID	Objective
01	Understand the practical applications of machine learning in classification of defects in aerospace materials
02	Replicate work of Aziz et al. [1] by creating a supervised machine learning model (kNN) to classify defects in additively manufactured Nickel Based Superalloy components, to verify the application of machine learning in defect classification.
03	Replicate work of Aziz et al. [1] by creating a unsupervised machine learning model (kNN) to classify defects in additively manufactured Nickel Based Superalloy components, to verify the application of machine learning in defect classification
04	Understand the structure of abradable coatings and understand what defects are present
05	Procure data for defects present in abradable coatings to be used in a machine learning algorithm
06	Use a supervised and unsupervised machine learning model to classify the defects present in abradable coatings
07	Evaluate the accuracy of both models at classifying defects present in abradable coatings.
08	Evaluate the precision of machine learning techniques in defect classification against presently employed methods

Table 1: Revised Aims and Objectives

Literature Review / Market Survey

1. What are abradable coatings and how are they used in Aerospace applications?

Abradable coatings are specialised engineering materials designed to endure wear and friction [1]. Created from various materials, they serve specific applications, particularly in aerospace, where they play a pivotal role in the seal coating system [5]. This system comprises an abradable seal coating for stationary components and abrasive coatings for rotating components, commonly utilised in the turbine and compressor stages of engines, as illustrated in Figure 1. The tip of the rotating component scrapes against coating particles on the abradable surface, causing them to disengage and exit the system [6]. Meticulous design ensures the particles can escape freely, preventing detrimental shear forces. As particles wear away, a new groove is formed, allowing a precise fit between rotating and stationary components, thus creating an effective seal coating system. The precise fit ensures maximum aerodynamic and thermodynamic efficiency of the system. Excessive forces, however, can lead to adverse consequences like blade tip heating and wear, potentially causing "titanium fires" in aerospace applications [5]. Achieving the ideal fit enhances overall system performance and aerodynamic efficiency.

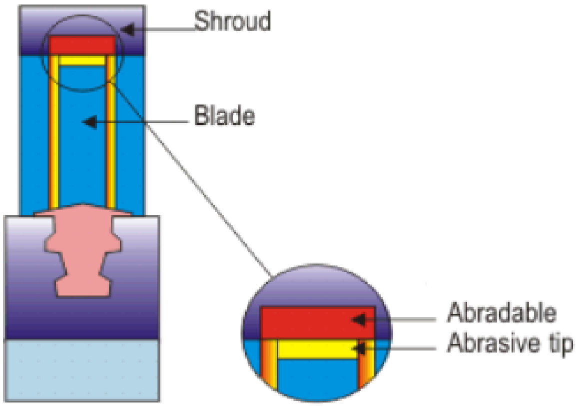

Figure 1: Schematic of abradable coating seal [6]

Metco 601, a widely used abradable coating by Oerlikon Metco, is tailored for clearance control applications [7]. Comprising aluminium-silicon polymer powder, it minimises wear on rotating components while optimising gas path efficiency. Widely employed in low-pressure compressors in turbofan machinery and automotive turbochargers, Metco 601's precise clearance control significantly contributes to machinery performance and longevity.

For temperatures exceeding 900 degrees Celsius, ceramic abradable coatings are suitable due to their higher operating temperature. Blade tips need reinforcement with adhered abrasive grit to cut through these coatings [6]. It's crucial to ensure that particles carry most of the energy when broken away to mitigate heat and reduce wear. Prolonged sliding without ceramic coating fragmentation can lead to melting wear, accelerating blade wear. The goal is intentional fragmentation upon contact to prevent continuous rubbing, reducing heating and material exposure, and preventing substantial damage from melting wear.

Abradable coatings extend beyond aerospace, finding application in stationary gas turbines, turbo compressors, radial compressors, turbochargers, pumps, and even biomedical engineering for bacteria contamination prevention [6-8]. This showcases their adaptability and significance across diverse technological applications.

2. Why do we care about the defects present in abradable samples?

The defects present in thermally sprayed abradable coatings are shown in Table 2.

Defect	Description
Pores	Voids or empty spaces within the material
Pits	Small depressions or cavities on the material surface
Cracks	Fractures or separations in the material
Crevices	Narrow gaps or spaces between two surfaces

Table 2: Defects typically present in abradable coatings [10-12]

The presence of defects significantly influences the performance of abradable coatings in several ways. For instance, defects catalyse coating damage by creating paths for electrolytes to infiltrate, hastening the chemical corrosion process [10]. This corrosion results in substantial material loss, surface irregularities, and diminished service life.

Furthermore, variations in thermal expansion rates between an abradable coating and substrate materials induce cyclic tensile and compressive forces, leading to crack formation. While small cracks can benefit the coating by serving as stress relievers [13], their growth can result in excessive material loss, eventually causing coating failure. Identifying and classifying cracks are vital steps in the analysis, offering valuable insights into the microstructure of abradable samples.

Defects within abradable coatings significantly impact their heat transfer capability, causing a reduction in the overall effective heat transfer coefficient of these materials [14]. When a sufficient number of defects are present, the system's temperature can rise to the point of melting, leading to system failure.

These examples illustrate how defects can adversely affect the performance of abradable coatings in seal coating systems, emphasising the relevance of new approaches in defect classification and detection.

3. What current methods are used to model the microstructure abradable coatings?

2D Image-Based Modelling

The current 2D image-based approach involves converting a microstructural graph of an abradable coating into grayscale. Figure 2 depicts a microstructural graph of plasma-sprayed Yttrium-oxide-partially-stabilised zirconia (Y-PSZ), with white pixels representing Y-PSZ and black pixels representing pores [16]. Components of the image can be generated using individual pixels or a mesh generation method. Emerging technologies, like resolution-adaptive mesh, enhance computational efficiency without compromising the Image Segmentation Model's accuracy, as seen in the red grid section of Figure 2. Using these components or mesh elements, mechanical properties, such as mechanical stress, heat flux, or thermal stresses, can be simulated.

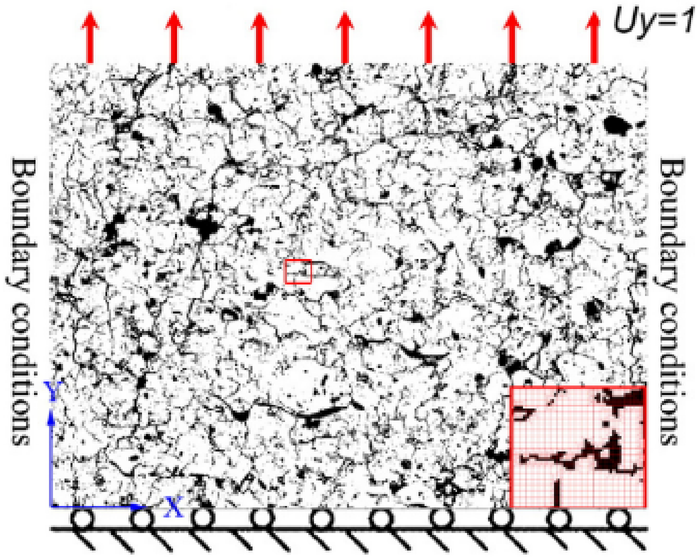

Figure 2: 2D microstructural graph, with illustration of resolution-adaptive mesh applied in region in red [16]

Accurate segmentation of scanning electron microscopy (SEM) images into maps describing the microstructure's phase locations is crucial for precise models [16]. Conventional threshold methods, designed for normally distributed peaks, may prove ineffective when numerous cracks are present. Cracks with intermediate brightness, as depicted in Figure 3, do not conform to a normal distribution, emphasising the importance of image brightness and quality in assessing data validity for machine learning models. Additionally, varying thresholds in Figure 3 demonstrate the impact on detecting finer details like small cracks and pores in the microstructure.

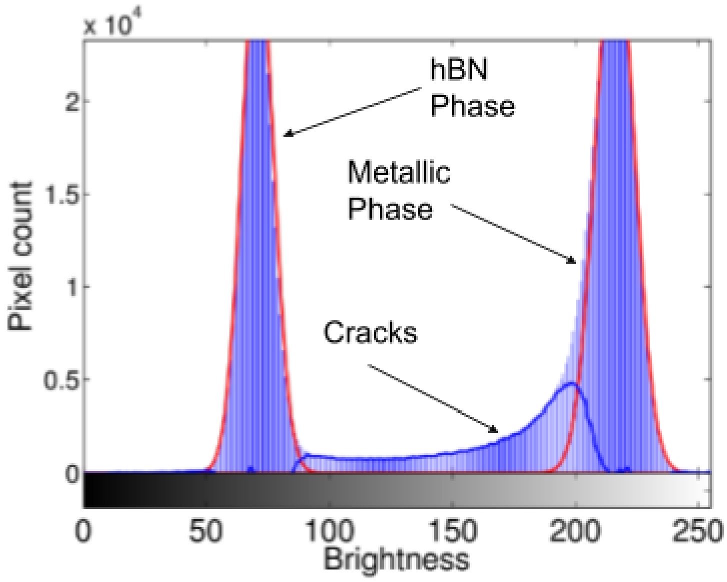

Figure 3: A histogram of an image of the 601-55 microstructure with normal distributions fitted to both peaks [4]

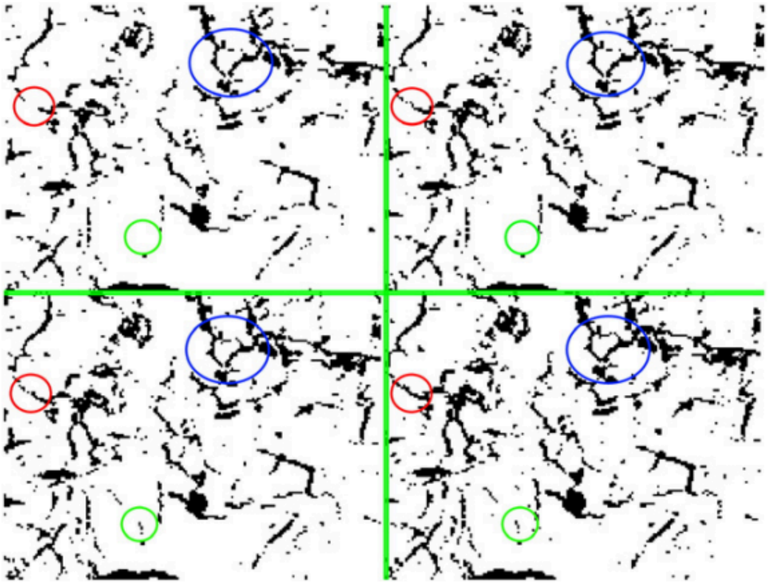

Figure 4: Comparison of microstructural graphs with different thresholds [16]

It is important to note that algorithms used to classify defects and different phases of materials in abradable coatings can depend on a variety of factors, including the number of phases in the sample.

3D image-based modelling

While 2D image-based modelling possesses capabilities, it encounters challenges in accurately simulating plane stress and strain [16]. Consequently, the adoption of 3D image-based modelling becomes necessary, as illustrated in Figure 5. The creation of 3D microstructure images for material samples can be achieved through X-ray tomography and serial sectioning. However, these techniques for generating 3D images come with inherent limitations, particularly in terms of image resolution. This implies that the chosen method for creating images in image-based modelling significantly influences the reliability of the data used for crack identification and analysis.

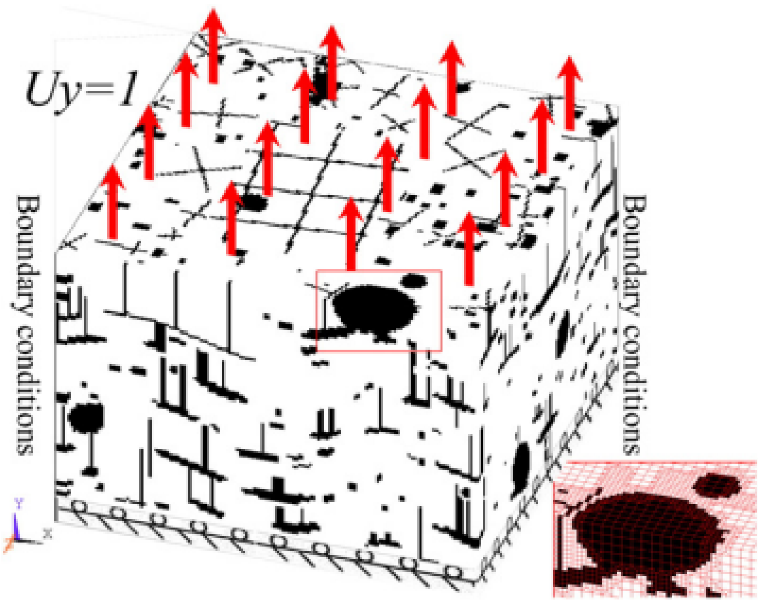

Figure 5: 3D problem definition and a magnified part of the resolution-adapted mesh for the contour region generated from SEM [16]

4. How are defects currently detected and classified in material samples?

Various techniques have been created for inspecting images to detect cracks or defects. However, these methods often overlook scanning electron microscope (SEM) images and are mainly tailored for identifying individual cracks in simple and uniform structures rather than extracting a network of cracks from a cross-section [4, 17-19].

Prior research has outlined the use of deep learning techniques in the detection of surface defects in material samples [19]. The research conducted by Bhatt et al. provides an overview of image-based surface defect detection techniques using deep learning, discussing various ideas associated with the topic.

The research team considered and classified a variety of defect detection problems that could be solved using deep learning techniques. These problems were classified as anomaly detection, targeted defect detection, concurrent detection of multiple defects and defect type clustering [19]. Then different types of machine learning were considered, namely supervised, semi-supervised and unsupervised. The researchers outlined the advantages and disadvantages of each of the types of machine learning with regard to defect classification problems previously mentioned. Considerations, such as type of data required and sensitivity to variation in data were also discussed for the various types of machine learning. Then, a variety of system architectures for defect classification, utilising deep learning techniques were discussed. This involves the discussion around image classification-based localization architectures, pixel-based localization, object detection-based localization. Finally the researchers recommended future research that needs to be completed, outlined in Table 3.

Research Topic	**Description**
Using deep learning with limited defect data	Acquiring a substantial amount of high-quality data can be challenging, especially in manufacturing, where the count of defect-free parts typically outweighs components with surface defects. To effectively train a deep learning model, it is crucial to have sufficient data of high quality. One potential solution to this challenge is the application of data augmentation. This technique involves introducing various transformations to the existing dataset to expand its size. These transformations may include alterations such as flipping, cropping, rotation, image mixing, random erasing, and colour space augmentation. Additionally, variations in image resolution or brightness can also be employed to enhance the dataset.
Explainability	In cases where a defect detection system either overlooks a defect or misidentifies a defect in an acceptable part, understanding the rationale behind these decisions made by the deep learning algorithm becomes important for users. Subsequent efforts should focus on enhancing the explainability of the observed system performance in future work.
Transfer Learning	Research should explore the development of versatile deep learning models applicable across multiple domains. For instance, designing a deep learning model capable of detecting defects in various materials sharing similar patterns and defect occurrences. This approach could prove particularly relevant for abradable coatings, given the diverse combinations of phases present in such coatings.
Finding balance between automatic feature detection and hand-crafted feature detection rules	Hand-crafted feature detection rules are dependable but come with the requirement of involving domain experts in defining features, which can vary based on the chosen paradigm (e.g., statistical, pixel-structural, filter-based, model-based). While adept tuning of these features yields effective defect detection algorithms, the process of collecting data from domain experts is often laborious and expensive, demanding

	considerable programming effort. Additionally, there's the ongoing challenge that new defects may emerge after initial data collection. On the other hand, automatic feature extraction offers a promising alternative, eliminating the need for the labour-intensive and costly expert-driven process. This approach also holds the potential to identify previously unseen defects. However, its effectiveness is contingent on having a substantial and well-balanced dataset that encompasses various factors such as noise, illumination, scale, and rotation changes. Striking a balance between these two defect detection methods is crucial for optimising performance and efficiency. Future research should delve into this delicate equilibrium, exploring ways to leverage the strengths of both hand-crafted and automatic feature extraction approaches for more robust and adaptable defect detection systems.
Scale invariant defect detection	While object detection architectures demonstrate precise defect localization in images, they encounter challenges in maintaining high accuracy when presented with images featuring diverse scales and distorted proportions. The struggle arises in effectively adapting to variations in scale and skewed perspectives, leading to potential accuracy limitations. Addressing these challenges is crucial for enhancing the overall performance and versatility of object detection architectures in defect localization across a broader range of image conditions. Future improvements should focus on refining the adaptability of these architectures to ensure robust and accurate defect identification under varied scaling and skewed scenarios.
Integration of physics-based reasoning	Deep learning, a statistical method, excels in predicting accurate models from data, with model learning contingent on data size and noise-to-signal ratio. In surface defect detection, images are influenced by conditions like lighting and exposure, impacting the reliability of the data. Physics-based reasoning, rooted in expert domain knowledge, transcends data dependency but has limited accuracy due to necessary simplifications. By combining deep learning and physics-based reasoning, one can mitigate noisy predictions, achieving accuracy across a broader regime while leveraging the strengths of both approaches. This integration ensures robust defect detection even in challenging conditions and varying data quality.
Avoiding overfitting	Training deep learning models involves adjusting numerous parameters automatically. If the dataset is significantly smaller than the number of parameters, overfitting becomes a risk. A balanced dataset is crucial. The most straightforward solution is to increase available data, either by acquiring more information or employing previously mentioned data augmentation techniques.

Table 3: Future Research Directions in use of deep learning for defect classification in materials [19]

Despite the fact that this paper refers to the use of deep learning techniques in surface defect detection, many of the concepts outlined are highly applicable to the detection of defects in the internal microstructure of engineering materials.

Current Status of Work

A substantial portion of the project's initial phase has been dedicated to a comprehensive literature review encompassing topics such as abradable coatings, machine learning, and the application of machine learning in defect detection and classification. During the training phase, the replication of Aziz et al.'s work underscored the superiority of the KNN classification algorithm in terms of accuracy.

While the primary focus has been on KNN and decision trees, there was an initial intention to explore other machine learning algorithms to identify potential improvements. Unfortunately, due to time constraints and the project's research-oriented focus, I haven’t been able to do this.

Navigating the machine learning model-building process with R has proven to be straightforward, aided by clear guidance from the recommended textbook. Additionally, prior experience with machine learning in MATLAB and Python has contributed to a familiar workflow.

The most intriguing findings thus far have arisen from in-depth research on abradable coatings and microstructural modelling gathered from various papers. Notably, insights from the work of Bhatt et al. on using deep learning methods for detecting and classifying surface defects have been particularly enlightening, and this knowledge remains highly relevant to the project's focus on detecting internal microstructural defects.

The current phase involves the challenging task of procuring the necessary data for training machine learning algorithms. Anticipated to be the most demanding and time-consuming aspect of the ongoing work, data procurement represents a crucial step in advancing the project toward its goals. I am hoping to procedure SEM pictures from the tribology research group at the University of Sheffield, as they have plenty of samples of abradable coatings. I also hope that the outcome of my dissertation may support them in their research projects.

Self Review

Over the course of this semester, the research process has been relatively straightforward, thanks to the guidance from my supervisor, Dr. Meurig Thomas, and the resources recommended to develop a solid understanding of machine learning methods using the R programming language.

Given my prior experience in software engineering and machine learning with MATLAB, I am confident in advancing the machine learning and software aspect of the project. However, a notable challenge has been the research of abradable coatings. Understanding this aspect has been difficult due to the scarcity of layman-friendly resources, with most literature being technically dense articles. Nevertheless, delving into the science of abradable coatings has been personally rewarding, especially considering my keen interest in turbines and compressors.

In terms of project management, progress has been slightly behind my initial expectations. Managing coursework from modules such as AER325 and AER380, along with commitments to Project Sunride and Project Hex, has proven challenging. Additionally, applications for further study and graduate schemes have added to the complexity of managing different commitments at once.

Project Management

Throughout the course of this semester, I have completed the first 3 tasks:

01	Understand the practical applications of machine learning in classification of defects in aerospace materials
02	Replicate work of Aziz et al. [1] by creating a supervised machine learning model (kNN) to classify defects in additively manufactured Nickel Based Superalloy components, to verify the application of machine learning in defect classification.
03	Replicate work of Aziz et al. [1] by creating a unsupervised machine learning model (kNN) to classify defects in additively manufactured Nickel Based Superalloy components, to verify the application of machine learning in defect classification

Table 4: Objectives completed in Semester 1

As expected, data collection is taking a significant amount of time. In addition, it has been challenging to find information about abradable coatings, due to the lack of textbooks or layman-term resources available. Because of these considerations, tasks 4 and 5 are still underway:

04	Understand the structure of abradable coatings and understand what defects are present in
05	Procure data for defects present in abradable coatings to be used in a machine learning algorithm

Table 5: Objectives currently underway

Once these tasks are completed, the final tasks can be completed. These are expected to be completed in Semester 2:

06	Use a supervised and unsupervised machine learning model to classify the defects present in abradable coatings
07	Evaluate the accuracy of both models at classifying defects present in abradable coatings
08	Evaluate the precision of machine learning techniques in defect classification against presently employed methods

Table 6: Objectives to be completed in Semester 2

Gantt Chart

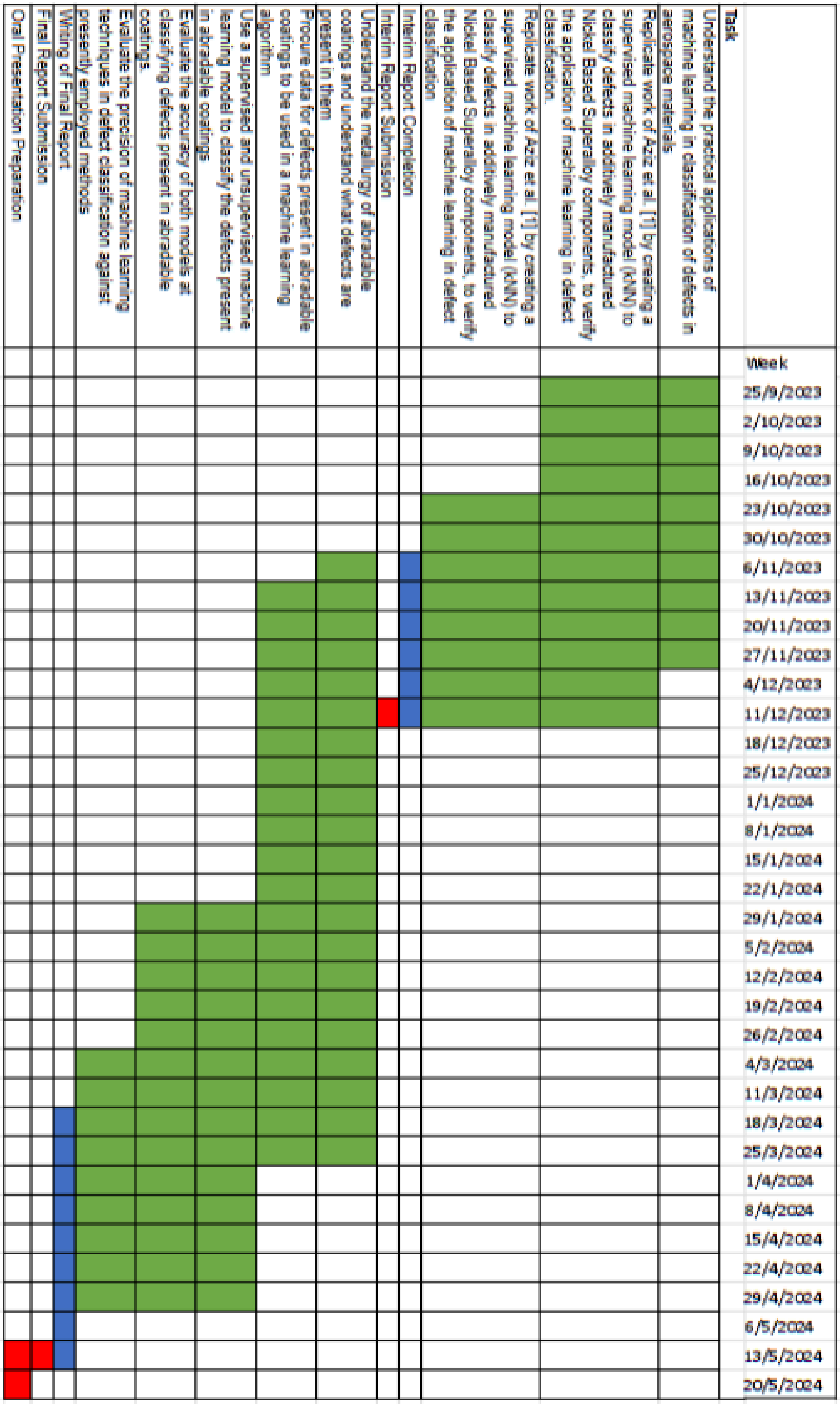

Figure 6: Gantt Chart representing Project Plan

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