Deliverable D 3.1

WP3 Report on case studies and analysis of transferability from other sectors

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Contents

Executive Summary

This deliverable reports on case studies and analysis of transferability to railways of approaches of artificial intelligence for predictive maintenance and defect detection. The document addresses transferability of AI techniques used for maintenance from related sectors to railways. It considers applications in Assets defect and faults detection and prediction, Vehicle Health Monitoring, Structural Health Monitoring, and Cybersecurity applications. In particular, transferability from the following related sectors will be surveyed and analyzed, starting from the results achieved in Work Package 1 (State-of-the-art) such as Aviation, Automotive, Manufacturing, Critical infrastructures (other than railways). Some of these sectors have experienced a faster progress due to higher research efforts invested in the last years in their development. Some examples are self-driving cars (e.g., Vehicle Health Monitoring), the paradigms of Industry 4.0 and cyber-security. Therefore, it makes sense to try to transfer and adapt the technologies and achievements of other sectors to railway transport. This document presents:

- proposed guidelines for carrying out transferability studies;
- identified relevant AI-based approaches developed in sectors different than railways;
- provided *indications* about transferability directions towards railway systems, focusing on railway safety and automation.

We introduce a **framework for transferability** to perform a structured transferability analysis of AI applications from other sectors to railways by setting general *dimensions*, and their derived *criteria*. Transferability dimensions and related criteria have been defined by considering: a) the outcome of the DISCOVER phase, which provides guidelines from the relevant stakeholders and from the analysis of the railway problems related to maintenance and inspection; b) the transferability analyses conducted in other sectors (e.g. [1], [2]). The considered criteria are congruence, significance, similarity, maturity and implementability. In particular, the following AI applications have been addressed: AI-aided fault diagnosis and prognosis through Digital Twins and IoT, AI-aided asset and bridge health monitoring based on autonomous UAV, Vehicle Health Evaluation based on Big data management (IoT-based) and Cloud Computing and Motion-based RUL estimation through non-intrusive sensors, Reducing malicious cyber attacks by using Cybersecurity Taxonomy Frame-work (CTF).

Further, several potential pilot case studies are proposed. These include applications for Level Crossings and Digital Twins for railway stations. It is expected that AI techniques for artificial vision based on deep learning used to automatically recognize patterns and detect anomalies in other sectors (e.g., medical diagnostics, security events, etc.) can be leveraged for defect detection and preventive maintenance also in the railway domain. Similarly, the Digital Twin representation of the real-system, a concept borrowed from predictive maintenance in mechanical engineering, could be used to allow real-time update of the models and on-line evaluation of defects and anomalies. It is worth mentioning that the smart maintenance applications discussed in this deliverable can be used to guide the execution of maintenance tasks. In fact, AI techniques can support fully or semi automated inspection activities and also build decision support systems aiming at indicating the most suitable maintenance activity that should be performed based on appropriate fault detection and pre-

diction. For instance, by predicting the Remaining Useful Life of a Level Crossing barrier, it would be possible to advise the replacement or specific maintenance actions aiming at increasing the RUL and system safety. Furthermore, a step-by-step decision support based on portable devices and augmented reality (such as the one enabled by smart-glasses) can be envisioned as a future development enabled by AI technologies. The proposed transferability analysis represents a first evaluation of the possible AI techniques that could be transferred to the railway sector, while specific proofs-of-concept will be developed to identify the advantages and benefits that AI could provide to railway maintenance and inspection.

Abbreviations and acronyms

Abbreviations / Acronyms	Description
ACO	Ant Colony Optimization
AI	Artificial Intelligence
ANN	Artificial Neural Network
API	Application Programming Interface
CBM	Condition-Based Maintenance
CCD	Charge Coupled Device
CI	Critical Infrastructure
CNN	Convolutional Neural Network
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DL	Deep Learning
DNN	Deep Neural Network
DoS	Deny of Service
DT	Digital Twin
EU	European Union
FFT	Fast Fourier Transform
FPS	Frame Per Second
GAN	Generative Adversarial Network
IBM	International Business Machine corporation
IDS	Intrusion Detection System
IIoT	Industrial Internet of Things
IoT	Internet of Things
K-NN	K-Nearest Neighbours
LC	Level Crossing
LED	Light-Emitting Diode
LSTM	Long Short-Term Memory
ML	Machine Learning
MRO	Maintenance Repair and Overhaul
NDT	Nondestructive Testing
NLP	Natural Language Processing
PCA	Principal Component Analysis
PdM	Predictive Maintenance
PHM	Prognostic and Health Management
PSO	Particle Swarm Optimization
RCM	Reliability Centered Maintenance
R-CNN	Region-based Convolutional Neural Network
RNN	Recurrent Neural Network
RUL	Remaining Useful Life
S2R	Shift2Rail
SHM	Structural Health Monitoring
SSD	Single-Shot Detector
SVM	Support Vector Machine
Ttable	Transferability Table

UAV	Unmanned Aerial Vehicle
VHM	Vehicle Health Monitoring
WP	Work Package

1. Background

The present document constitutes the Deliverable D3.1 “WP3 Report on case studies and analysis of transferability from other sectors” of the S2R JU project “Roadmaps for AI integration in the Rail Sector” (RAILS). The project is in the framework of Shift2Rail’s Innovation Programme IPX. As such, RAILS does not focus on a specific domain, nor does it directly contribute to specific Technical Demonstrators but contributes to Disruptive Innovation and Exploratory Research in the field of Artificial Intelligence within the Shift2Rail Innovation Programme. The RAILS research is structured in three main phases:

- DISCOVER, covering all the preliminary survey and analysis activities.
- ASSESS, covering all the core development and experimentation activities.
- LEARN, covering all the follow-up and knowledge dissemination activities.

The work carried out in WP1 (State-of-the-art of artificial intelligence in railway transport) achieved the following objectives: i) to provide an in-depth review of the current research on the application of Artificial Intelligence (AI) in railways and of AI techniques and methods, ii) to build a first map of AI technologies to solve railway problems or improve performance in railway scenarios, iii) to identify specific needs and railway application areas for future research, iv) to point out the major open problems and challenges for AI adoption according to the current research and the railway stakeholders, v) to determine some priority directions and provide preliminary recommendations.

Starting from the findings and the application areas identified in WP1, the objective of the ASSESS phase is to define pilot case studies and develop proof of concepts leading to a technology roadmapping for an effective pick-up of AI in the rail sector. To this aim, the ASSESS phase includes three technical workpackages that investigate different railway domains but have the same task structure. The first step of the ASSESS phase is an analysis of AI applications from other sectors in order to enable transferability studies, and the identification of possible case studies. The case studies are not specifically aimed at transferability but they are the context of the technical activities carried out in the workpackages. Transferability is just one of the aspect that will be addressed.

Specifically, RAILS Project Work Package 3 addresses Artificial Intelligence (AI) techniques to support smart maintenance in railways, and in particular:

- Novel approaches to enable preventive and condition-based maintenance by data analytics and machine learning, leveraging on emerging technology like the Industrial Internet of Things (IIoT) for sensing and actuation. In fact, the vast amount of data generated by networked monitoring devices, like drones and Wireless Sensor Networks (WSN), need to be collected and interpreted to generate useful information and knowledge. That allows to replace the traditional approaches based on planned maintenance schedule and hence improve effectiveness and efficiency in defect detection and problem repair.
- Self-healing approaches based on the paradigms of autonomous and self-adaptive systems.
- Advanced techniques based on Deep Neural Networks (DNN) and Convolutional Neural Networks (CNN) to support real-time identification of defects through artificial vision

enabled by smart cameras and other smart-sensors.

- Digital Twin paradigm applied as a run-time predictive model, based on the multi-formalism integration and cross-checking of diverse AI models.

This Work Package also leverages on the results of the Shift2Rail IP3 research project named IN2SMART (Intelligent Innovative Smart Maintenance of Assets by integRated Technologies).

2. Objective

This deliverable addresses transferability of AI techniques used for maintenance from related sectors to railways. In particular, transferability from the following related sectors will be surveyed and analyzed, starting from the results achieved in Work Package 1 (State-of-the-art) such as:

- Aviation
- Automotive
- Manufacturing
- Cybersecurity
- Physical security and surveillance

Some of those sectors have experienced a faster progress due to higher research efforts invested in the last years in their development. In turn, that derived from higher flexibility and expected higher return on investment. That is especially true if one considers the expectations coming from self-driving cars (e.g., Vehicle Health Monitoring) and the paradigms of Industry 4.0. Another sector where AI is experiencing a fast progress is cyber-security, where antivirus/antimalware, intrusion detection and prevention systems use heuristics based on anomaly detection as well as misuse detection to recognize both known and unknown threats. Therefore, it makes sense to try to transfer and adapt the technologies and achievements of other sectors to railway transportation. In particular, it is expected that AI techniques for artificial vision based on deep learning used to automatically recognize patterns and detect anomalies in other sectors (e.g., medical diagnostics, security events, etc.) can be leveraged for defect detection and preventive maintenance also in the railway domain. Similarly, the Digital Twin representation of the real-system, a concept borrowed from predictive maintenance in mechanical engineering [1], will be used to allow real-time update of the models and on-line evaluation of defects and anomalies.

3. Introduction

Transferability studies aim at investigating the extent to which research findings or new technologies can be applied in other contexts. As such, this document reports the activities carried out in this direction by:

- proposing guidelines for carrying out transferability studies;
- identifying relevant AI-based approaches developed in sectors different than railways;
- providing *indications* about transferability directions towards railway systems, focusing on railway safety and automation.

Determining whether research findings and/or technologies can actually be transferred from one context to another is a complex activity that cannot be performed within the time span of a limited analysis. Therefore, here we report the work performed to take a first step towards such an objective. This first step will help to design proper roadmaps to transferability scenarios. In particular, for the analysis, we focus on sectors that are close to railway transport and are expected to provide higher level of research developments and/or suitable for transferring to railways. These cover transport modes including Avionics, Automotive, and Maritime, and non-transport sectors including Manufacturing, Machinery, and Critical Infrastructures, taking into account both cyber and physical concerns.

The remainder of the report is as follows. Chapters 4 and 5 report on research findings and technologies currently available in other transport modes (other than railway) and non-transport sectors, respectively. Chapter 6 introduces a framework for transferability analysis and establishes relationships between the Chapters 4 and 5 and the proposed directions. Notably, the results of this analysis are still *perceptions* of transferability/applicability, they provide indications but need to be verified through proper research. Chapter 7 identifies possible pilot case studies, taking into account both the potential that emerged by the activities carried out in task 3.1 and the needs expressed by the railway community according to the outcomes of WP1. The primary objective of the case studies is provide the context in which some transferability activities can be developed. Lastly, Chapter 8 summarises the findings of these activities.

4. AI-based Emerging Technologies for predictive maintenance and defect detection in other Transportation Sectors

Recently a series of studies related to predictive maintenance have been deployed and the aim of these projects is to define and propose innovative solutions utilising the intelligent distributed maintenance system gives support to the process of the systematic preservation activities.To be more specific, identifying unexpected behaviours from massive amount of equipment sensors data, and turning them into machine-understandable and actionable insights for the downstream tasks of proactive asset protection — preventing the potential accidents with predictive perception beforehand [3]. That is the essential idea of predictive maintenance or intelligence forecasting, Which puts its stress on scheduling maintenance and repair actions before failure of functioned equipment occurs.

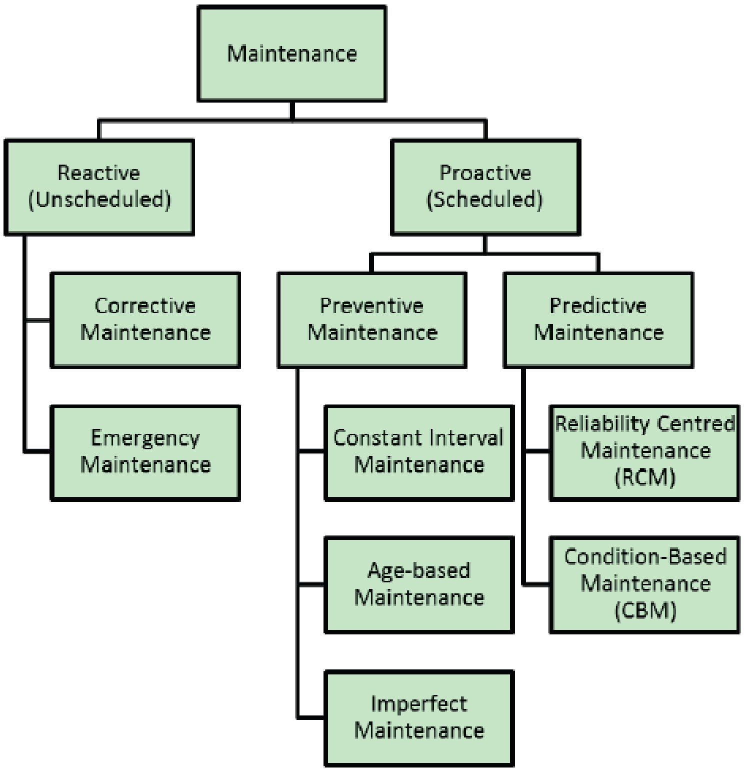

Fig. 4.1. the classification tree for the current types of maintenance. Inspired by [4]

As we can see in Figure 4.1, the general categories of maintenance in transport can be summarised as Reactive maintenance and Proactive maintenance, what we want to reduce is the occurrence of Reactive maintenance, which is unscheduled and maintenance engineers need to perform maintenance service after the failure occur. While Proactive (or scheduled) maintenance can be seen as a more cost-saving paradigm that contains preventive maintenance and predictive maintenance, to perform maintenance at predetermined intervals to reduce the probability of failure, and replacing components or systems according to in-service equipment condition respectively [4].

The underlying industrial framework for predictive maintenance models is relatively uniform irrespective of applications [5]. Such architecture usually located on multiple function layers, with different objectives at each layer but featured with highly coupling characteristics and showing a strong sequential dependency between these layers [6]: data acquisition, data transformation, data/asset evaluation, decision support layer and human interface layer. Predictive maintenance employs various of techniques in the architecture described. Continuous development in cloud/edge technology and distributed intelligent systems, allows embedded smart equipment to aggregate information from the whole industrial assets and creates new possibilities for storing data with various data types — either it is the fix-sized grids information (e.g. images) or sequential signals (e.g. speech/voice records). However, converting those raw data into a readable and well-structured knowledge such that they can be directly leveraged by machine learning models seems to be a challenging task. Many maintenance leaders are looking forward a novel paradigm based on a concept called prescriptive maintenance [7], where machine learning tools and artificial intelligence techniques not only predict potential failures but also contribute to the process of identifying solutions and thus to make specific recommendations for equipment maintenance. Prescriptive maintenance analytics can speed up overall production outputs, the time to make a product and find a feasible solution can be decreased, and reducing labour density and utility costs [8]. Specifically, it would continuously reassess the implemented models (files trained to recognise specific patterns) and data to automatically generate possible actions based on the analysis results which is unachievable by human analysts within limited time period. Compared with preventive maintenance and predictive maintenance, prescriptive maintenance takes the analysis procedure a notch higher by predicting failure events, calculating and anticipating potential outcomes when a recommended action is performed. The remaining parts of this chapter are not going to be limited to introduce those strategies of the data transformation, but diagnostic evaluations towards the procedure of defect detection would be discussed. As an important output, we would investigate how AI-based technologies significantly contribute to the non-railway sectors, especially in those transport-related domains such as aviation (Section 4.1), automotive (Section 4.2) and ship transportation (Section 4.3).

4.1. Aviation

It is a fact that nowadays aircraft generate more data than ever and around 2 million of terabytes of data were generated by the global fleet, through various flight data recorder and aircraft health monitoring [9]. On the one hand, the a huge amount of information have been digitised with an ever-growing manner. On the other hand, the financial cost of sensors, data storage and data communication has significantly dropped over the latest few decades. Which means that a lot of emerging data need to be investigated and explored. Incorporating effective Big data and Data mining techniques in seems a novel attempt to overcome the challenge since manual analysis is impractical anymore [10].

An essential subject within Big Data analysis and Data mining is predictive maintenance. These AI-based technologies are mainly used to collect and condition data from one or more sources, which essentially digitise and process raw data and make these data readily available for storage and subsequent actions. Physical parameters, such as sound, light and temperature, to voltage current and other electrical signals can be converted by signal conditioning to digital values. Other formats of data van be obtained from diverse sources, e.g. object identification radars, GPS, video detectors, social medias and so on. For example, Condition-based maintenance (CBM) [11] is such a method by using the historical accident records/flight logs that contain a lot of hidden information including reasons of the worst aircraft disasters. A deep analysis of existing predictive maintenance models with the context of aviation shows that the combination of historical incident data with already applied maintenance methodologies can largely improve the performance of existing and new analytical models for an advanced predictive maintenance [12]. Most of them have been attributed to a faulty or overlooked maintenance.

However, one of the significant challenges for implementing predictive maintenance in current aviation industry is that providing access authority to the available data and to perform any desired analysis. That is to say, on-board avionics systems are primarily designed for assisting the fly operations rather than gathering test data for other usages. Additionally , many systems do not have the necessary sensors installed to provide data such as temperature, pressure or vibration information. This may result in insufficient data available to support predictive maintenance analysis.

Prognostic and health management (PHM) is a paradigmatic framework to ensure the safety, reliability and maintainability of aircraft by considering the possible challenges we listed above. Such paradigm contains several components including condition assessment, fault diagnosis, and remaining useful life (RUL) prediction[13]. As we can see in Figure 4.2, this novel concept of prognostic and health management is essentially an engineering system integration of diagnostics, prognostics and aircraft health management.

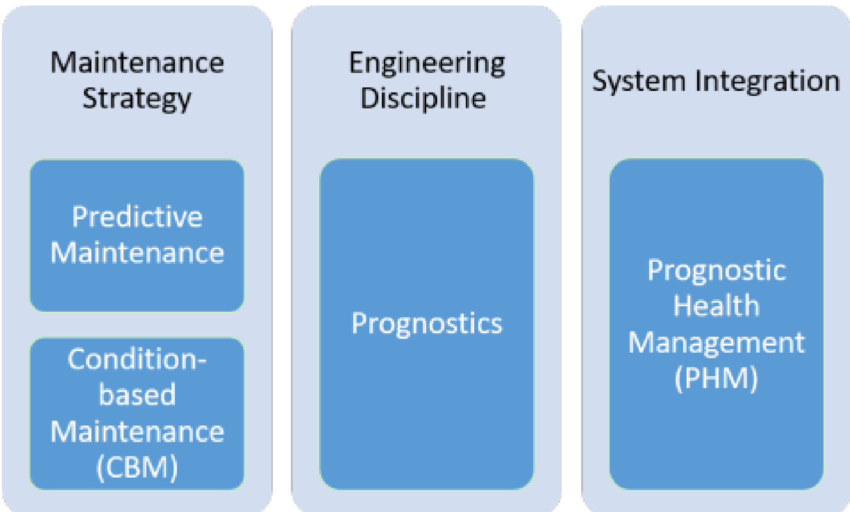

Fig. 4.2. the relation between PHM and relevant terms. Inspired by [13]

According to [14], aircraft maintenance is a comprehensive concept, including routine maintenance, repair, overhaul, defect inspection and modification, to retain an aircraft as well as the related aircraft systems/components in a serviceable and reliable condition. Aiming to create revenue as the physical deterioration throughout aircraft's life would be minimised. Predictive maintenance techniques especially PHM are designed to help assess the condition of on-board equipment and to estimate when and how the maintenance should be performed. While Prognostics in this framework act as an engineering norm related to the prediction process that supports the practice of predictive maintenance with advanced fault detection capabilities and accurate lifetime prediction capacities. In the practical perspective, the **AE-based (Acoustic Emission-based) sensors** have been applied to the wing section of the specimen, and non-visible damage. Based on which the extent of damage and its propagation path can be predicted with the physics-of-failures based model [15]. Other industrial non-visible damage detection methods include **radio-graphic testing (RT)** and **magnetic particle inspection (MPI)**. Compare to AE-based sensor method, they are both nondestructive examination (NDE) techniques that the former involves the leverage of either the intensity of x-rays or gamma rays would attenuate differently when penetrating each internal structure of a component while the later considering that since these cracks, folds, inclusions are non-ferromagnetic, they have a high resistance to the passage of magnetic lines of force. However, firstly, the cost of X-ray film and other equipment is relatively high, and the inspection speed is slow. It is only suitable to detect volume defects such as pores, slag inclusions, shrinkage holes, etc., and it is not easy to find small cracks. The later method only suitable for ferromagnetic materials and it's difficult to determine the depth of defect. After the magnetic particle inspection the components need to be demagnetised and cleaned. All these drawbacks show the necessity of introducing an effective approach to this field, and the practices already proof that AI-based method can largely address the challenges brought by traditional solutions. E.g. Digital Twins has helped a lot to improve the maintenance capabilities of airline operators, they also help reduce the costs and contribute to delivering a better experience to the passengers. Many aerospace companies have begun to utilise digital twins to accomplish the goal of reducing unplanned downtime for plane engines and other essential supportive systems [16], which helps airlines to keep aircraft in service for a longer duration.

Condition-Based Maintenance (CBM) As we said before, CBM is the application that based on operational running data and machinery condition to determine when the maintenance should be performed. In the project of [17], it aims to investigate how a condition-based maintenance approach can be implemented in an industrial context and a method that can assist companies in their implementation efforts using OSA-CBM (Open System Architecture for Condition-Based Maintenance) data model was developed.

In the figure 4.3 shown above, the general architecture of a CBM system consists some functional layers, including data acquisition, data manipulation, state detection, health assessment, prognostic assessment, and advisory generation. Each of these block has its unique sequence and the information flow exactly from bottom layers to upper layers. Another challenge for this framework is to incorporate different types of maintenance tasks within one single complex system, for satisfying ever-growing industrial demand. Thus, Adhikari and Buderath [18] proposed an RCM-based maintenance framework which mixed with CBM and preventive strategies. The framework has been implemented and is demonstrated with a case study. Additionally, airline operators can perform proactive and predictive maintenance to increase platform operational availability and efficiency, extend its useful life cycle and hence reduce its life cycle cost. Specifically, some digital twins [19] are capable of mitigating damage or degradation by activating self-healing mechanisms or by

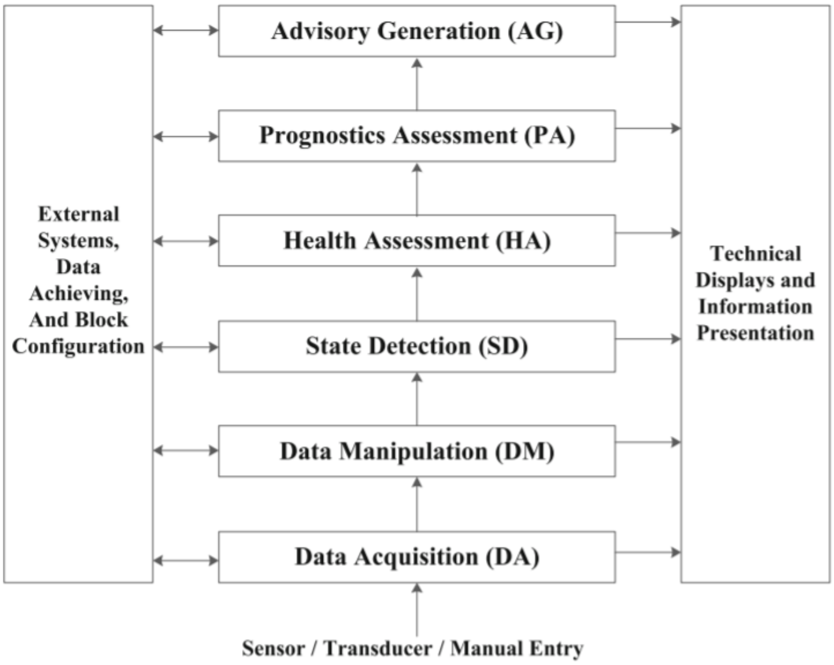

Fig. 4.3. Systematic framework and information flow for CBM. Inspired by [17]

recommending changes in the mission profile to decrease loading, thereby increasing both the life span and the probability of mission success. Moreover, applications of digital twins make it possible to predict the remaining useful life of the asset with a high level of accuracy. For instance,in the digital twin of the landing gear [20], sensors are placed on typical failure points: hydraulic pressure and brake temperature.

ReMAP is an effective solution of Real-time Condition-based Maintenance for Adaptive Aircraft Maintenance Planning. Its main objective is to promote transition from current preventive and reactive aircraft maintenance to a condition-based approach. That allows air transport decision makers to perform a near-optimal scheduling of aircraft maintenance. For failure prediction and estimation of the remaining useful life for systems and components, ReMAP used a hybrid approach combining data-based machine learning algorithms and physic-based models. Advanced methodology such as federated learning is being applied in order to guarantee data confidentiality. In the federated analytics, data estate would be the owner of data where algorithms travel back and forward and training the machine learning algorithms is done iteratively allowing models can be collaboratively trained by different airlines, air manufacturers and MRO companies for different aircraft. Being a large and complex system in each flight a single aircraft produces a large volume of data which is used in PHM algorithms, in order to reduce the burden of transferring these large data from aircraft to external service. ReMAP is applying edge-computing technologies, in which some initial computations using the data are done at the edge. e.g. On the sensor—on-board computing framework. This approach offers a possibility for a faster alarm generation in the case of sudden degradation of the system or component health. The calculated remaining useful life is conveyed to the end users (e.g. maintenance engineers) at the right time. The visualised reports containing actionable information developed in the ReMAP project. This will then be included in the ReMAP maintenance decision support tool to support the maintenance crew to take decisions efficiently in the aircraft maintenance process. Also, this will result in shorter troubleshooting time, higher aircraft availability and costs savings. Nevertheless, one limitation to AI is that machines/automation computing units are often do not know what they did not learn. While AI is implemented to understand and interpreting large volumes of information, there is no guarantee that the technology will understand all the data. We are expecting intelligent equipment behaves more like humans and infers sufficient knowledge based on the learned information but at the current stage the above described applications are not likely to achieve this goal.

4.2. Automotive

In the automotive industry, or commonly known as 'road transport', ensuring the functional safety within the product's life cycle while minimising the costs of equipment maintenance has become a significant challenge. This field is one of the prime examples that showing how data-driven (ML-based) methods has revolutionised an industrial sector, fulled by the transformation of the traditional vehicle into an increasingly complex intelligent system ([21]). The aim of this section is to provide a broad range of readers an overview on ML-enabled predictive maintenance applications in automotive field. According to [22], in intelligent transport systems, data can be obtained from diverse sources, such as smart cards, videos, sensors, novel technologies units, and so on. Using advanced sensor and detection techniques, massive amount of real-time transportation information can be acquired and processed to make sure these data are capable for the downstream prediction and maintenance tasks.

As we introduced in Section 4.1, prognostics and health management (PHM) framework has been regraded as an effective methods to access the health condition and reliability of systems for the purpose of maximising operational reliability and safety. Compared with the PHM in aviation, this framework would work functional in commercial vehicle sector, by reducing the maintenance cost and downtime while also improving the reliability of vehicle components can have a major impact on performance of the whole fleet, and hence business competitiveness. A feasibility study of designing and implementing PHM systems in commercial vehicles has been conducted by [23], where the On-Board Diagnostics (OBD) systems can be used to evaluate the health of vehicle components. For example, a discrete hidden Markov model was proposed by [24], for detecting manifold air leakage issues in the air-intake system, and thus approximate the health status for gasoline engines. An experiment performed on a 1.3L production vehicle engine and the result of On-board Diagnostic platform shows that the air leaks can be effectively predicted through the proposed model.

Video cameras are widely deployed in intelligent road transportation systems. A good demonstration is the development of advanced traffic management system (ATMS), in which the video image detection systems (VIDS) are good alternative compared with traditional sensors for practical tasks such as vehicle identification and traffic flow detection. For example, in the study of [25], freeway imaging sensors that use massive video data have been successfully deployed to carry out incident detection and have shown high accuracy on traffic flow estimation compared with other conventional image acquisition methods. The accurate vehicle video data can be further processed to improve the prediction performance of general transportation demand regrading vehicle emission models [26].

Generally speaking, various formats of data like vehicle speed, vehicle density in a certain area, traffic flows and trip time for a specific vehicle were mostly collected by several kinds of traditional sources: on-road sensors, floating car sensors and wide area sensors [27]. Traditional roadside sensors include inductive magnetic loops [28], pneumatic road tubes [29], piezoelectric loops and microwave radars [30]. However, new generation roadside sensors such as ultrasonic and acoustic sensor systems, magnetometer vehicle detectors, infrared systems, light detection and ranging (LIDAR) and video image processing and detection systems are gradually employed with the recent great development of detecting theories/technologies. Another significant data resources for intelligent automatic transport system is the floating car data (FCD), or commonly called as ”On-board data”. The major characteristic of such data were collected by the embedded sensors in vehicles. The on-board sensor techniques have been largely developed in latest few decades so nowadays the popular FCD sensors such as automatic vehicle identification (AVI), license plate recognition (LPR) are playing a more decisive role in data collection of mobile car information. In order to let AI functional, models need to be trained based on the collected data. However, ”On-board” data brings a few obstacles to this case: In most companies, data is typically siloed and rarely consistently catalogued and governed. Without good-quality training data, a company will find it quite hard to get an AI application implemented. That is to say, companies need to determine whether the data has the right parameters. Organisations are also responsible for making sure that their data is able to be shared with different companies based on federal, state, and internal requirements. This is another challenge we need to consider when talking about standards and regulations.

A novel conceptual innovation named connected and autonomous vehicles (CAV) appears in front of the public recently, which combines radical changes of vehicles design and their interactions with the road infrastructure. CAVs have the potential to vastly improve road safety by liberating the human driver out of the heavy driving tasks. However, the systematic evaluation of their safety concerns has been an essential challenge due to the lack of real-world CAV exposure data. Several studies have attempted to simulate CAVs by exploiting either a single or integrated multiple simulation platforms. For example, [31] developed a CAV control algorithm allows a CAV, for the first time, to have a good ability on longitudinal control, searching adjacent vehicles, and identifying nearby CAVs so that lateral decisions based on a rule set can be made.

Next we would specifically focus on ML-based Predictive Maintenance for automotive systems. This part would largely remedy the research gap of survey of ML-based PdM for automotive systems with a focus on vehicle in operation. Table 4.1 give the information about what these related work are and the essential topics they addressed.

As we can see in the summary table, Ali Y.H.[32] majorly focuses on the recent novel innovations in the field of vehicle acoustic emission signal analysis through AI tools in machine condition monitoring and fault diagnosis. While Bhargava C.[34] and Alsina et al.[33] investigated a series of papers with a wide range of reliability prediction for the on-board electronic elements compared with different AI methods. Deep learning approaches for

Reference	Focused topic
Ali Y.H.[32]	AI-based acoustic emission signal analysis in condition monitoring and fault diagnosis
Alsina et al.[33]	ML techniques for reliability prediction of vehicle components
Bhargava C.[34]	AI for reliability prediction of electronic components
Carvalho et al.[35]	ML-based techniques for predictive maintenance
Khan and Yairi.[36]	Deep learning in system health management

Table 4.1: Overview of related work

evaluating/monitoring the health condition of machines and the health management for the whole system have been discussed by Khan and Yairi.[36].

4.3. Maritime

In the recent years, we have found that the concept of Predictive Maintenance (PdM) has been broadly investigated and applied among the industry of aviation and road transportation (Section 4.1 and 4.2), as an effective guideline in improving the performance of on-board equipment, reducing probability of failure, and estimating the remaining useful lifetime (RUL). Nevertheless, this perception has not been sufficiently considered in the field of shipping industry as the procedures of ship maintenance have not been regarded as an area needed of expenditure [37]. However, maintenance in maritime is importance not only because it can undermine the sustainability of marine eco-system but also put a burden on the overall profitability of shipping company.

According to [38], the advocates of revolution argue that a move from the prescriptive and rule-based maintenance strategy to a data-driven, risk-based approach may lead to the maintenance more reliable and efficient. The evolution of mainstream maintenance policy was heavily based on technical and economical considerations [39]. That is to say, more and more studies have applied Condition Based Maintenance (CBM) scheme in increasingly complex machinery system and the ever-growing parameter monitoring data regarding equipment conditions, due to which costs lower revenue yet greater availability for ship systems. Such trend can be seen in the study of [40], in which authors initiate a innovative CBM-based solution by using a computational artificial intelligence model, for analysing the historical records of vessel's engines and compressors health condition.

The core of CBM policy is to monitor and collect conditions data from equipment. Compared to other transportation industry, several issues could be ignored during the data acquisition process [41]. Firstly, the evolution and appearance of new-designed equipment makes historical values obsolete. secondly, data pooling is not always effective because even similar equipment in various conditions may have different failure patterns. Technological advances and higher cost of possessing data assets driven the demand for testing and implementing intelligent approaches as a subsidiary to existing condition monitoring paradigm, and it was found that ANNs (artificial neural networks) are seen as one of the most promising techniques in this regard. According to [42], a neural network can be defined as a comprehensive processing unit that consists of a massive of parallel distributed micro-processors, which has the features of human perception for storing experiential knowledge and making it capable for decision making process. One of the advantages of ANNs is that it provides an effective analysing tool to understand and simulate the nonlinear behaviour of complex systems and it can be used as a valuable performance assessment tool for operators and decision makers. ANNs are capable to learn from past examples and capture the essential functional relationships among date especially these relationships are hard to describe. which makes it more suitable for modelling and forecasting nonlinear time series applications. Specifically, Noor et al. [43] introduced a ANN model on the context of marine diesel engine system and this network was derived from the standard back-propagation Levenberg-Marquardt training algorithm, in which various engine speeds and loads as the input data, aiming to predict its output torque performance, the power of break, break specific fuel consumption, and exhaust gas temperature. Results showed that the overall prediction accuracy of ANN model was significantly higher than that of mathematical model. In addition, [44] also applied a dynamic auto-regressive neural network for estimating the exhaust gas temperature within the future 5 hourly period on a cylinder of a marine diesel engine. The predicted values have been validated with the ground-truth actual data and there is little difference between them.

However, in many cases, the performance of neural network-based models have the limitation of bad interpret ability due to it is difficult to contribute a failure of the system or its components to specific causes. on the other hand, the results are too complex to be properly understood by humans, explainable AI (XAI) approaches are necessary to make the reasoning process and the outputs more understandable by shipping operators and engineers [45]. Under this concerns, hybrid approaches are emerging recently and preferred as an effective solution to support the process of failure prediction and fault diagnosis.For example, Lazakis et al. [46] provide a systematic paradigm that incorporates Fault Tree Analysis (FTA) and Failure Mode and Effects Analysis (FMEA), such that critical main engine systems/components and their corresponding parameters to be monitored and identified. Based on the study of Pascual and Galar. [47], the FTA can be conducted in a qualitative or quantitative manner, depending on the available data type. Qualitative analysis is typically useful in identifying what combinations of events cause the top (visible) event to occur. Besides the FMEA framework, Lazakis et al. [48] presented a predictive maintenance strategy in their work that combines Failure Modes, Effects & Critical Analysis (FMECA) with FTA by considering the existing ship maintenance regime as an overall strategy including technological advances and decision support system. A novel ship maintenance strategy is also developed by Turan et al.[49], which implemented a criticality and reliability assessment and the FTA tool used time-independent dynamic gates to effectively illustrate the correlations of the components for a diving support vessel. Differently, Cicek and Celik [50] proposed a framework of FMEA individually to monitor and reduce the occurrence probabilities of crankcase explosion failure in order to improve machinery system reliability and enhance operational safety for on-board ship equipment.

5. AI-based Emerging Technologies for predictive maintenance and defect detection in non-Transportation Sectors

AI-based maintenance includes several tasks such as fault forecasting/prediction, defect/anomaly detection, and prognosis (i.e. the estimation of the Remaining Useful Life - RUL). To address these tasks, it is necessry to constantly monitor and manage the health status of the systems under examination to collect data and characterise their behaviour. In 2018, Khan and Yairi [51] proposed a cross-domain literature review on the application of deep learning in system health management; they raised some challenges that, in our understanding, have not been addressed yet. Although DL-based maintenance applications help to improve safety aspects and reduce ongoing maintenance costs, they produce an increase in the complexity of the system which could lead to a decrease in reliability [51]. Additionally, they also highlighted other shortcomings, that can be considered as actual especially in the railwyas, including the lack of appropriate benchmarking of the proposed solutions and the lack of explainability (as we have already mentioned in Deliverable D1.2 [52]). Similarly, in 2019, Carvalho et al. [53] proposed a cross-domain systematic literature review focusing mostly on ML approaches for predictive maintenance (PdM) rising mostly the same concerns for: i) the need of sensing techniques to improve data (quality/quantity) collection; ii) works comparing the proposed PdM strategies to different ML algorithms; and iii) the creation of datasets to be used as comparative benchmarks. Both the aforementioned studies carried out comprehensive reviews without focusing on a specific application domain; indeed, they considered various scenarios including rotating machinery, bearings, wind/gas turbines, and pumps. Lastly, reference [54] proposes a review on modern computer vision models for defect detection based on Deep Learning. Object detecors architectures (e.g. the YOLO and the R-CNN families) were considered and, despite there is not a “rule of thumb”, the authors identified in the YOLO family, especially the latest architectures (e.g. YOLOv4 [55] and PPYOLO [56]), the best approaches to get proofs-of-concept in this scenario as they have great generalisation properties and can perform at a high FPS rate. Then, among others, a technical problem was emphasized: limit the data transfer from acquisition sensors and cloud systems as it might be quite time-consuming. The solution they propose is to adopt on-board computation such as the Intel Neural Compute Stick or the Nvidia Jetson family.

Among non-transport sectors, Healthcare is undoubtedly one of those that have benefited most from the development of AI. AI systems help to reduce diagnostic errors that are mostly unavoidable [57]. AI systems, whether based on Machine Learning [57] or Deep Learning [58–60], have already shown great potentials in predicting diseases, detecting cancers, identifying possible treatments, and medical imaging in different healthcare subdomains including pathology, radiology, and dermatology. Actually, image-based diagnostic systems are those that have found the greatest benefits since the advent of AI [58]; notably, in this context, DL-based applications have shown expert-level diagnostics accuracy [59]. Interestingly, also AI-based NLP applications have been extremely useful to understand and classify clinical documentation and published research to assist clinical decision making; for the sake of knowledge, the pioneer system IBM Watson includes both ML and NLP modules to support and recommend treatments in the context of cancer diagnosis showing great potentials [57, 61]. However, the above-mentioned studies also report some problems AI-based systems must cope with to have an impact in clinical practice including: i) ethical/privacy implications as these systems relies on patients data; ii) temporality and domain complexity as diseases progress and change over time in a non-deterministic way; iii) biased data as the effectiveness of a model depends on the population sample considered in the training phase; iv) interpretability as, especially in this domain, there is the need for a clear explanation for the output of a model. It was necessary to introduce a domain so technologically advanced, however, in our view, other sectors such as manufacturing, machinery, and critical infrastructures have more similarities with the railways.

To better understand what can be reused and transfer in the railway sector, in terms of both data and approaches, in the remainder of this chapter we analyse separately the evolution of AI-based solutions in domains that are not transport-related such as Manufacturing (Section 5.1), Machinery (Section 5.2), and Critical Infrastructures (Section 5.3) by evaluating some of the most recent surveys.

5.1. Manufacturing

In manufacturing, defect detection is crucial during the quality control phase [62]. Notably, mainly Machine Learning techniques, especially Deep Learning for Computer Vision, have been tested in this field. Recently (December 2020), Yang et al. [62] published an interesting comprehensive review on Deep Learning for Defect Detection highlighting its strengths and weaknesses compared with "traditional" defect detection technologies such as ultrasonic testing, machine vision detection, magnetic powder testing, osmosis testing, Eddy current testing, and X-ray testing. Among them, Machine Vision could rely on Machine Learning and Deep Learning approaches but is limited to surface defect detection only; however, it can be automatised and has high accuracy. In this context, the authors introduced some Deep Learning architectures, whose strengths and weaknesses are reported in Table 5.1, and emphasized the opportunity to employee object detection deep architectures (Table 5.2) as defect detectors.

Besides that, what is also interesting is the survey on the current **defect detection equipment** involving, among others, *LYNX industrial vision system, IRNDT infrared thermal imaging testing, smart U32 ultrasonic scanning detector, parts appearance optical detection equipment, sealing detection equipment, and 3D visual measuring equipment*. Lastly, in our understanding, Yang et al. [62] suggest focusing on the following aspects: i) embedded sensor equipment for real-time defect detection; ii) integrate methods for multi-modal defect detection; iii) move towards 3D defect detection (e.g. using colour cameras) to detect also shape defects and not only surface defects; iv) improve image quality acquisition (less noise, good light conditions); v) reuse defect information to optimise online the production process (self-correcting machines).

In the context of DL-based visual inspection, in 2018, Sun et al. [63] conducted a review for steel products. This could be very useful to **understand how data can be processed and what could be the best solution for image acquisition and environment lightning**. Departing from the specific problems of the analysis of steel materials (e.g. the specific

Method	Strengths	Weaknesses
Convolutional Neural Networks	Strong learning ability for high-dimensional input data and can learn abstract, essential, and high-order features.	The good expression ability and the calculation complex will increase with the increase of network depth.
Autoencoders	Good object information representation ability. Can extract the foreground region in the complex background. Good robustness to the environment noise.	The input and output data dimensions must be consistent.
Residual Neural Networks	Lower convergence loss and does not overfit, so it has better classification performance.	The network must cooperate with deeper depth to give full play to its structural advantages.
Full Connected Neural Networks	It can extract the feature of any size image, and obtain the high-level semantic prior knowledge matrix, which has a good effect on semantic level object detection.	The feature matrix transformation combined with the underlying features is needed. Slow convergence speed.
Recurrent Neural Networks	With fewer sample data, it can learn the essential features and reduce the loss of data information.	Increasing the number of learning iterations could cause overfitting.

Table 5.1: Strength and weaknesses of Deep Learning Models. Obtaining readapting Table 2 in [62]

Methods	One-Stage OD (e.g. YOLO family, SSD)	Two-Stage OD (e.g. RCNN family)
Functioning	The input image is processed directly to obtain the position coordinate value and category probability. The position is corrected thereafter.	Candidate regions are extracted from the input image through selective search and region generation network. Then, convolution, pooling, and other processing are conducted to obtain feature maps.
Advantages	In the case of the low input separation rate, the speed and accuracy can be balanced simultaneously, and the detection speed is fast (above 45 FPS).	The deep semantic features of the object can be obtained. High detection accuracy even with small objects or scenes with high density
Disadvantages	Low accuracy for small objects and prone to miss detection, low positioning accuracy.	The algorithm has a large volume, large amount of stored data, complicated calculation process, and slow detection speed.
Processing	Real-time.	Non Real-time.

Table 5.2: Object Detectors for defect detection. Obtaining readapting Table 3 in [62]

types of defects), the authors identified three possible **image sensors**: charge coupled devices (CCD), which could be both linear array or area-array camera, complementary metal oxide semiconductor devices (CMOS), and *smart cameras [64, 65] which are equipped with appropriate hardware (e.g. processor and memory) to process a large amount of data in advance*. Linear array CCD cameras were selected as the best choice for industrial purposes as they could meet the frame rate requirements, i.e. the frame rate of the camera must be greater than the speed of the object. Then, the authors also presented **different kinds of illumination sources** such as optical fiber, LEDs, and stroboscopic xenon lamps; LEDs are indicated as the best option as they have a good colour performance, high luminous intensity, and a wide spectrum range. Moreover, they also analysed the lightning methods (how to position cameras and lights). Lastly, concerning data processing/transformation and defect detection, the survey performs a wide-spectrum analysis on both traditional and learning-based methods. Mostly the same survey structure was then adopted by Li et al. [66] to survey defect detection methods in textile manufacturing in 2021. Based non these reviews, without meant to be exhaustive, we could draft a picture (5.1) representing the possible methods that can be applied for surface defect detection in these fields (steel and textile products).

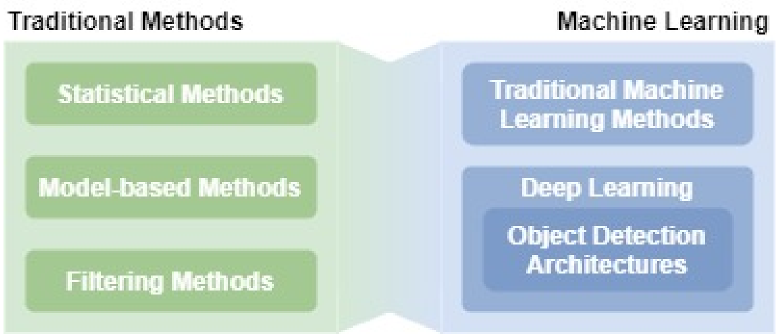

Fig. 5.1. Methods for steel and textile products Defect Detection. Inspired by [63] and [66]. *Statistical Methods*: e.g. mathematical morphology, co-occurrence matrix. *Model-based Methods*: e.g. Markov Random Fields, Fractal Models. *Filtering Models*: based on e.g. Sobel, Canny, and Laplacian filters, or Fourier, Discrete Cosine, Gabor, and Wavelet transform. *Traditional Machine Learning Methods*: e.g. Decision Trees, SVM, K-NN. *Deep Learning*: e.g. Convolutional, Full Connected, Residual, and Recurrent Neural Networks. The latter also includes *Object Detection Architectures*: e.g. SSD and those belonging to the YOLO or the Region-based CNN families.

Notably, *traditional methods can be used to* ***transform data (i.e. extract features or pass to another domain)*** *and combined with ML approaches to detect defects*. For the sake of knowledge, references [63] and [66] provide some examples: gray-level co-occurrence matrix combined with SVM [67], or Markov Random Fields combined with K-NN [68] to detect defects in steel products; Discrete Cosine Transform combined with ANNs [69], or Gabor features combined with Fuzzy ANN [70] to detect defects in textile products.

In addition, Li et al. [66] also made some consideration on the correlation between hardware for data collection and methods to be used. The suitable algorithm should be chosen based on the type of data collected, whether, for instance, from thermal cameras or visual tactile sensors. What also was highlighted is: i) the need of collect a sufficient amount of data to cope with unbalanced defects categories, perhaps adopting data augmentation techniques (e.g. collect the same image from different angles or different light conditions); ii) the need to implement multi-scale object detectors (i.e. capable of detecting defects with different sizes) with high accuracy and good real-time performances; and iii) the opportunity to apply AI-based techniques to predict possible defects in advance and reduce the quality control workload (e.g. [71]).

Mostly the same concept expressed in the latter point was addressed by Meng et al. [72] in the context of Additive Manufacturing. CCD cameras images, acoustic events, and thermal data in combination with ML approaches can be exploited to optmise the processing parametes, i.e. parameters adopted during the production phase (e.g. printing speed, layer thickness). Typically, multiple samples are printed to be tested and thus ensure product quality; Machine Learning is seen as a solution to reduce these experimentation by analysing the data related to the desired property of the product and predicting a set of processing parameters to be adopted to obtain such a result. As an example, by leveraging CCD droplets images, an ANN has been adopted to determine the optimal voltage level and thus adjust the voltage of the system to control the droplet jetting behaviour [73]. In addition, ML can also be employed for geometric error compensation, e.g. by using thermal data and some processing parameters to feed a CNN to predict geometric distortion which is then used to achieve error compensation [74]. According to the survey findings, ML models are capable of identifying the relationship between processing parameters and desired properties of the product in output, and deal with images and acoustic emissions to detect defects formation in real-time. Nevertheless, to this aim, it is important to collect enough data or, as an alternative, adopt active learning methods.

Typically, with enough data, supervised approaches could be used to detect defects and, in case of the adoption of Deep Learning, the need for feature engineering drastically deceases (or disappears); however, when dealing with unbalanced datasets (e.g. when the defective class has much less sample in respect of the non-defective one), other approach should be consider as might be more effective. This facet also emerged from the review conducted by Bhatt et al. [75] on Deep Learning approaches for image-based surface defect detection. Here, several architectures were classified and analysed, also taking into account the learning paradigm (e.g. supervised, semi-supervised, and unsupervised). In a domain like manufacturing, datasets may be very unbalanced, as non-defective samples are much easier to collect and, additionally, always new defects can occur during the production process; thus, anomaly detection-oriented approach can be used to detect defects quite efficiently [76]. Alternatively, it is possible to adopt transfer learning (e.g. by leveraging pre-trained networks as feature extractors [77, 78]) or data augmenting solutions (e.g. by cropping some regions from defective images [79] or exploiting GANs [80]).

To conclude, different studies can be found regarding Digital Twins for industry and smart manufacturing applications [81–83]. In brief, a digital twin is the virtual counterpart of a physical system that evolves with it by leveraging IoT sensors, mathematical models, etc. Therefore, IoT is one of the fundamental enabling technologies for Digital Twins as it allows them to be a real-time representation of the physical system. In the context of manufacturing, Digital Twins have been mostly exploited to optimize different aspects of the product manufacturing process and the process lifecycle [82]; they produce a virtual representation of the manufacturing asset (i.e. manufacturing machinery and tools) from which data can be easily retrieved and exploited to perform AI-based predictive maintenance and fault diagnosis.

5.2. Machinery

It is now widely accepted that AI, jointly with the Internet of Things (IoT) paradigm, has brought many advantages in the industrial field, especially when it comes to machinery health assessment and data acquisition. Industrial IoT (IIoT) – defined as "the network of intelligent and highly connected industrial components that are deployed to achieve high production rate with reduced operational costs through real-time monitoring, efficient management and controlling of industrial processes, assets and operational time" [84] – is currently seen as one of the pillar technologies to constantly monitor industrial machinery and processes to achieve **real-time data collection** and move towards Industry 5.0. As interesting enabling technologies for IIoT, *blockchain, cloud computing, big data analytics, and Artificial Intelligence* play an important role [84]: the **blockchain** allows a distributed, traceable, and secure data sharing among all the entities involved in the IIoT; **cloud computing** clearly allows a suitable computational power to analyse the massive growth of data in IIoT; **big data analytics** involves tools and techniques to efficiently manage and analyse the massive amount of data streams; lastly, **Artificial Intelligence** allows the autonomous run and interaction of IIoT entities besides the fact that it plays a central role when it comes to predictive analysis, anomaly detection, fault diagnosis, and so on. Tailored on the usage of AI as a supporting technology to increase reliability and safety of industrial systems, there is plenty of studies in the literature addressing, among others, AI-based machines fault diagnosis [85,86], but also more narrowed analyses on the bearing component [87–89].

Liu et al. [85] proposed a review on AI-based fault diagnosis of rotating machinery. As also discussed for the manufacturing field (Section 5.1), different signal processing methods can be adopted jointly with AI techniques to extract features from raw data such as time-domain analysis (e.g. mean, variance, kurtosis estimation), frequency-domain analysis (e.g. FFT, bispectrum analysis), and time-frequency analysis (e.g. short-time Fourier transform, Hilbert-Huang transform, wavelet transform). However, given the exponential increase of data streams, data fusion methods and dimensionality reduction approaches might be more suitable for data pre-processing [85]. For example, reference [90] applied data fusion to reduce the number of vibration sensors, reference [91] proposed a composite spectrum data fusion approach to increase the performances in rotating machines fault diagnosis, and, lastly, in references [92,93] data fusion and principal component analysis were combined for fault separation and diagnosis. Lastly, reference [85] also gave some useful remarks about the performances of different ML-based techniques in the context of rotating machinery fault diagnosis which are summarised in Table 5.3: notably, SVM, ANN, and deep learning approaches (mostly autoencoders and deep Boltzmann machines in this case) tend to perform better in terms of accuracy, whereas k-NN and Naive Bayes approaches are much more explainable and have clear physical meaning.

	ANN	*SVM*	*k-NN*	*Naive Bayes*	*DL*
Accuracy	3	4	2	1	4
Classification speed	4	4	1	4	2
Robustness to noise	2	2	1	3	4
Robustness to overfitting	1	2	3	3	3
Robustness to parameters	1	1	3	4	2
Explainable physical meaning	1	1	3	4	1

Table 5.3: Performances of ML-based algorithm for rotating machinery fault diagnosis [85]

Similarly, Lei et al. [86] reviewed ML-based approaches for machine intelligent fault diagnosis (FID). Concerning **data collection**, different sensory is typically involved to constantly collect data for specific applications, for example: vibration data are mostly used for bearings and gearboxes fault diagnosis; acoustic emission data are used for bearings and gears deformation detection; speed data are commonly used to detect engines faults; and, lastly, current data are involved when it comes to electric-driven machines. In addition, the authors created an interesting chart depicting the advancement of ML-based technologies which is reported in Figure 5.2. This development is due to some shortcomings of the traditional ML methods, which are now widely accepted in the literature, encompassing the manual and engineered/expert feature extraction and selection, and the fact that the traditional ML techniques are not appropriate when it comes to big data scenarios due to advent of IoT and the massive volume of data they bring. Beyond the traditional ML methods, which are almost the same as those mentioned in [85], it is interesting to emphasise that CNNs have been used also to process one dimension (1D) data such as vibration/current data, mostly when these are subject to shift-variant characteristics. Lastly, to cope with the lack of labelled data, transfer learning and generative (e.g. GAN) approaches were identified as the most suitable techniques that, based on the achieved results, will surely be suitable solutions also in the future.

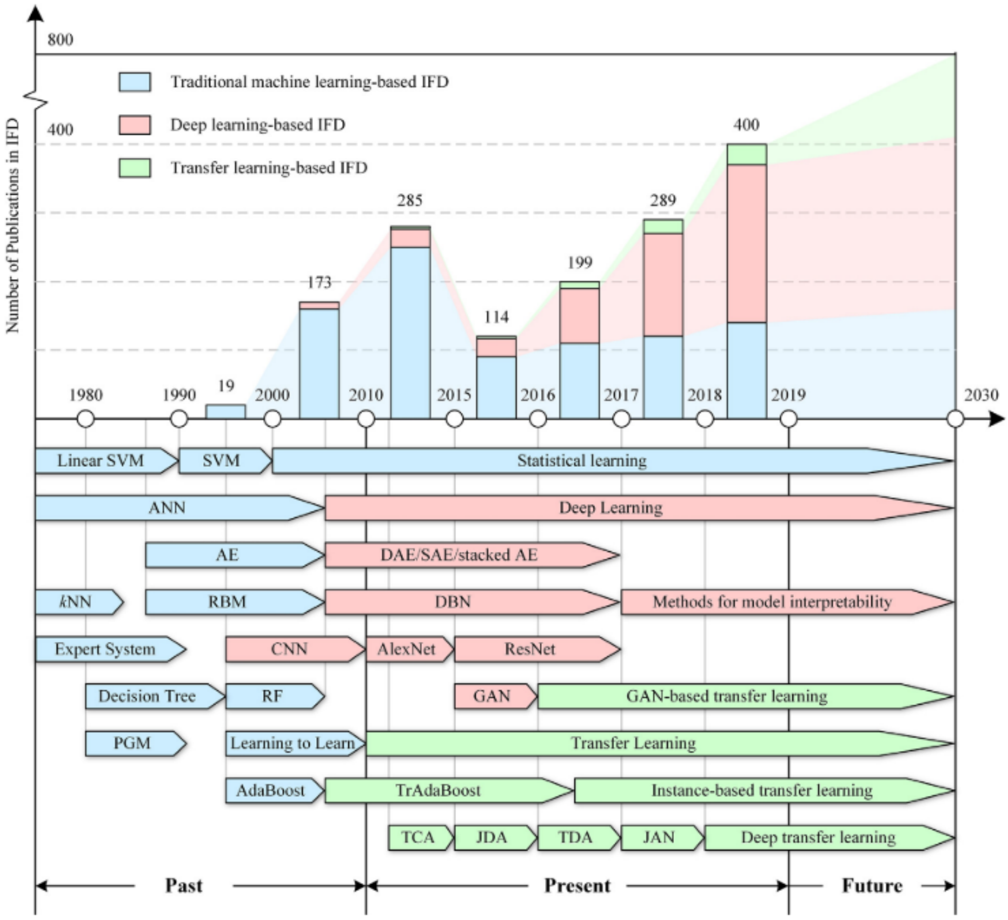

Fig. 5.2. The advancement of ML-based solutions [86].

Besides what has been discussed so far, some studies mainly focused on AI-based bearings fault diagnosis in rotating machinery [87–89]. Also in this case, Deep Learning has been widely adopted, and almost all the approaches have been exploited (e.g. 2D CNN, 1D CNN, autoencoders, RNN, GAN). Notably, [89] mainly focused on condition monitoring and predictive maintenance by analysing, among others, studies addressing the Remaining Useful Life (RUL) estimation of bearing for which very different approaches were used in the literature such as SVM, ANN, CNN, and RNN (which are particularly useful when it comes to analyse time-dependent data). However, the most of these approaches are based on laboratory analysis, considering noise-free data. Lastly, [88] also surveyed some **bearing fault datasets** that might be useful also in the railway domain in combination with transfer learning approaches: the Case Western Reserve University (CWRU) bearing dataset [94]; the PRONOSTIA bearings accelerated life test dataset [95], tailored for RUL estimation; and the Intelligent Maintenance System (IMS) dataset [96], which also involves human-made (artificial) bearing faults.

To conclude, also in the context of machinery, Digital Twins have had a good impact in estimating their RUL and health status. Actually, also what has been written in Section 5.1 about Digital Twins in manufacturing may fall within the machinery field as there the goal was to assess machines and tools functioning. Anyhow, we have also found other AI-based RUL estimation applications leveraging Digital Twins including turbofan engine performance degradation [97] (by exploiting the NASA's C-MAPSS dataset) and bearings degradation [98] (by leveraging vibration signals and a simulation-based Digital Twins). Lastly, it is also worth noting that Digital Twins open up countless cross-domain opportunities towards a safer health assessment as it is possible to carry out different simulations starting from the real status of the physical system without affecting its operability, for example through fault injection techniques [99] (i.e. by introducing faults in the digital model to study and predict its possible behaviour).

5.3. Critical Infrastructures

Critical Infrastructures (CIs) encompasses such sectors and assets that are "essential to maintain vital societal functions [100]" including power grid, transport network, and information and communication systems. Hence, any damage (or even their destruction) both human-induced and natural (e.g. earthquakes) may result in unpleasant consequences for the security of countries and their citizens [100]. Clearly, railway assets fall within the CIs, however, we have already widely reviewed AI solutions adopted in the rail sector within the deliverables published so far and discussed transport sectors in Chapter 4. Therefore, in the following of this section, we focus on both cyber and physical infrastructure protection by analysing the evolution of Artificial Intelligence in the field of cybersecurity and structural health monitoring.

5.3.1. Cybersecurity

As mentioned in Section 5.2, IoT has contributed to the development of more interconnected and cohesive environments producing many advantages when it comes to, among others, structures/components on-line monitoring and real-time data collection. However, at the same time, IoT and other technologies such as cloud computing have contributed to "open" these cyber-based systems as now there are more possible entry-points; hence, cybersecurity is now playing a highly central role when it comes to systems/infrastructures protection [101–105]. At the same time, although AI has brought many "positive" advantages, also attackers have benefitted from it; cyberattacks are becoming more complex, smarter, and are constantly evolving over time. Consequently, traditional and static control measures are not so effective anymore and new solutions, whether based on new paradigms (e.g. Digital Twins [106]) or AI (or maybe both), are needed to ensure the competitive protection of cyber-physical infrastructures.

Cybersecurity can be defined as "the set of technologies and processes designed to protect computers, networks, programs, and data from attack, unauthorised access, change, or destruction" [107]. Reference [105] taxonomically subdivided cyber threats and possible defence measures/processes. Without going deeper with details, cyber threats encompass misuse of resources, malware, denial of services, and user, root, and web accesses compromise; concurrently, defence measures include all the possible means capable of detecting or predicting such threats such as firewalls, antivirus, and Intrusion Detection Systems (IDSs). It was found that AI, particularly in the form of ML and DL, has had a significant impact in improving these kinds of systems [101–103, 105, 107]. To support IDSs, there are two main analytic processes: [103, 107]: *misuse detection*, which requires that the attack signatures are known (so the dataset must be labelled), and *anomaly detection*, which models the normal behaviour of the system and aims to identify abnormal deviations. The former is surely most effective than the second, but requires that the attacks are known; the latter produces more false alarms but can be effective to detect unknown threats (e.g. zero-day attacks). This is why, in many cases, a *hybrid approach* is preferred and IDSs usually have two modules implementing both of them. Additionally, IDSs can be classified in host-based intrusion detection systems (HIDS) and network-based intrusion detection systems (NIDS) [103], depending on the system under monitoring. To **collect network data** and build NIDSs, networking devices such as switches and routers are typically involved; differently, HIDSs relied on log files [103]. Actually, **packet data can be also collected** through pcap APIs monitoring physical interfaces (e.g. Ethernet port) on host systems [107]. Besides that, there are various **datasets available online** that can be exploited to build DL-based approaches for intrusion detection, reference [105] has provided an overview for some of them including: KDD Cup 1999 (DARPA1998), Kyoto 2006+, NSL-KDD, ECML-PKDD 2007, Information Security and Object Technology (ISOT), HTTP CSIC 2010, CTU-13 (Czech Technical University), ADFA Linux, UNSW-NB15, UNB-CIC. The latter encompasses multiple datasets: Android botnet, botnet, CIC DoS, Tor-nonTor (ISCXTor2016), and UNB ISCX VPN-nonVPN.

The aforementioned studies propose different surveys on the usage of AI in cybersecurity reporting that almost any kind of ML approach has been investigated to cope with cyber threats. **Traditional ML approaches** like Decision Trees, SVMs (also one-class SVM), Association Rules, Naive Bayes classifiers, Bayesian Networks, Clustering approaches (e.g. K-means, DBSCAN), K-Nearest Neighbors, Artificial Neural Networks, Ensemble Learning approaches (e.g. AdaBoost, Random Forest), but also Evolutionary Computing methods (e.g. PSO, ACO) have been exploited to detect intrusions or classify attack types (e.g. DoS, Probe or Scan, Remote to Local, User to Root). Reference [107] made an interesting analysis on the effectiveness of some of these approaches: for anomaly detection, one-class SVMs or density-based clustering methods (e.g. DBSCAN) are the most suitable; differently, for misuse detection, decision trees, random forest, genetic algorithms, and rule-based models are preferred as they are capable of generating readable signatures. However, ML did not result so effective as Deep Learning in this domain for two main reasons. In the first place, traditional ML relies on feature extraction/selection as the algorithms work with pre-determined features, however, it is very complex in cybersecurity to recognise significant features of, for instance, unseen attacks [102]. Additionally, without a proper feature selection, models may misclassify some attacks and the training would be time-consuming [103]. Secondly, massive data coming from multiple sources are continuously stored and, typically, there is a high variability due to new vulnerabilities, therefore, models need to be constantly updated to cope with the concept drift [105].

Deep Learning is capable of detecting nonlinear correlations in the data and easily identify unknown attacks such as advanced persistent threats (APTs) and zero-day attacks; additionally, **DL approaches** do not require feature extraction and are able to handle large datasets (both in terms of samples and features). The authors in [103] proposed a DL-based approach for intelligent intrusion detection that exceeded the capabilities of traditional machine learning methods; comparative analyses were performed considering both binary and multi-class classification problems and leveraging four well-known datasets (KDDCup99, NSL-KDD, UNSW NB-15, and WSN-DS). Other possible approaches that have found great applicability in this field are CNNs, Deep Belief Networks, RNNs (including LSTM which proved to be very effective in detecting temporal correlations of various attacks, such as DoS, command injection, and malware), Autoencoders (including variants such as deep denoising autoencoders) [102, 105].

However, there are some **problems specific to cybersecurity** which are mostly related to the datasets and the processing/training speed domain and prescind from the exploited approach. Firstly, data labelling is fundamental but very time-consuming given the amount of data generated daily; labels are necessary both in misuse detection, to distinguish the features related to the different attacks, and anomaly detection, to identify the entries related to the normal behaviour of the system [107]. Secondly, given the high variability of the attacks, not only the labelling but also the model training should be carried out periodically; this means that ML or DL models, differently from other applications where they are trained once and used without any issues for a long time, should have a low training time to be retrained, ideally daily, to incorporate the features of new possible threats [107]. To partially solve the latter problem, self-adapting models, or models that can be trained incrementally (i.e. that do not require complete retraining from scratch), can be adopted. Thirdly, understandability is necessary to understand the characteristics of the detected attacks. Lastly, generalisation performances must be taken into consideration and solutions must be provided to cope with the concept drift due to new attacks that may invalidate the effectiveness of the models; the concept here is that if a model works properly in a given instant, it is not said that it will work properly also when the characteristics of the attacks change [104].

Lastly, it is necessary to mention that **AI-based systems themselves are prone to be attacked** [102, 104, 105]. For the sake of knowledge, attacks to the ML-based systems may belong to the following categories [105]: poising attacks (training phase) and evasion attacks (test/inference phase). Posing attacks aim to inject adversarial samples in the training set to distort the model training and decrease its classification (detection) performances at test time; such kinds of attacks can be mitigated, for example, purifying the training set by implementing some adversarial sample detection mechanism, or by implementing robust learning mechanisms, i.e. by adopting techniques depending on robust statistics which are less sensitive to outliers. On the other hand, evasion attacks consist in fabricating adversarial samples capable of evading the detection system given some information of the ML system or data used to train it; in this case, possible countermeasures include adversarial training (active learning techniques aiming to retrain the model on adversarial attacks), feature transformation (i.e. feature selection, insertion, and rescaling), and game theory or robust optimisation (also known as smoothing model outputs, which formulates the adversarial issue as a min-max problem between attackers and defenders). Notably, Deep Neural Networks are very vulnerable to adversarial samples, and even the minimum modification may compromise the system. In this case, there are different possible approaches to increase the reliability of the system including: i) adversarial training, as explained above; ii) defensive distillation, according to which the output of a first DNN is fed into a second DNN to prevent a sort of well-fitting on training data (so perturbations are less effective); iii) pre-processing or denoising input, which consists in transforming the data before feeding them to the network as to suppress adversarial noise; iv) architecture alteration, i.e. introducing additional architectural components (e.g. layers) to the classical DNN architectures; v) network verification, which involves a sort of samples analysis to verify its compliance with the network's properties; vi) ensembling counter-measures, i.e. combine multiple defence systems in parallel or series; vii) adversarial detection, i.e. implementing another system which detects adversarial samples through anomaly detection or binary classification.

5.3.2. Physical infrastructure monitoring

As already mentioned above, new technologies such as IoT and cloud computing have contributed to interconnect components and systems in a cyber-physical space which can be exploited to improve prognostic maintenance. Traditionally, maintenance activities were conducted on a scheduled base but, afterwards, risked-based methods were increasingly adopted to prioritize critical equipment; an example is the recommended practices for the introduction of risk-based inspection (RBI) for oil and gas [108, 109] designed by the Americal Petroleum Institute [110]. Subsequently, the advent of AI is moving the spotlights towards predictive maintenance (PdM) and prognosis and health management (PHM), i.e. towards the prediction of the health status of the system and the estimation of their remaining useful life (RUL) [110].

However, even though it is possible to *collect massive data thanks to the IoT-based sensors*, only a finite collection of datasets is over and over exploited by the researchers; therefore, it can be said that there is a sort of lack of collaboration between industries and the academia, or, these collaborations are restricted by confidentiality reasons [110]. However, AI for PdM and PHM is one of the most popular topics in recent years, whose main process goes through three phases, as described in Fig. 5.3. This is a generic process, which can also be practically shared with the approaches described in Section 5.2 where machinery-related AI-based applications were analysed. Data-related problems are mostly the same; collecting qualitatively good data and properly analysing them is not so straightforward in many cases. Large number sensors collect multi-dimensional data which are difficult to handle without data fusion techniques or dimensionality reduction; sensors need to be monitored and calibrated, additionally, noises need to be continuously corrected; systems are not allowed to fail, in many cases, therefore, it is not possible to collect "negative" samples; lastly, in real life, machines are subject to a constant evolution of the environmental conditions [110].

Focusing on structural health monitoring, failures can be generally classified into two categories [111]: soft failures, which derives from a gradual accumulation of damages occurring during the infrastructures operability, and hard failures, caused by catastrophic

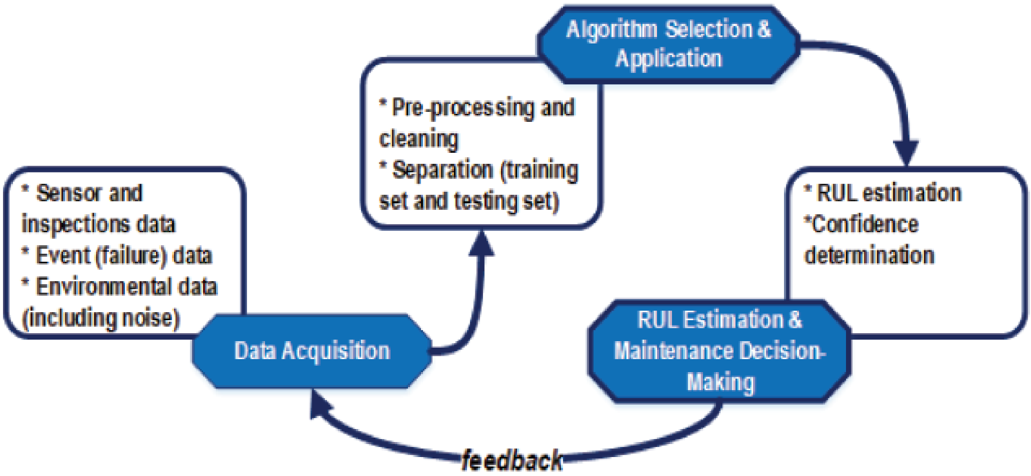

Fig. 5.3. AI-based process for PdM and SHM [110]

events both natural or artificial (e.g. heartquakes, tornado, explosions, terrorism). The latter prescinds from constant monitoring of the specific infrastructure as they are caused by external threats which need to be predicted by applying methodologies that consider multiple factors that go beyond the infrastructures; differently, soft failures may be predicted by involving monitoring sensors and building models to analyse the infrastructure remaining useful life. ***Data for physical degradation analysis*** *typically come from nondestructive testing (NDT - including acoustic emission, eddy current, infrared thermographic testing, leak testing, magnetic testing, strain, radiographic testing, ultrasonic testing, and visual testing) and structural health monitoring (SHM) sensors (including contact sensors such as accelerometers, fibre optic sensors, and ultrasonic wave sensors, but also non-contact ones such as cameras)* [111, 112]. For the sake of knowledge, NDT approaches have been exploited in multiple non-transport domains for many prediction applications including [111]: nuclear heat exchanger tubes corrosion damage detection leveraging eddy current data; or civil infrastructure monitoring such as bridge, pipeline, and concrete structure inspection. However, NDT are off-line methods and inspection data are often scarce, unbalanced, subject to measurement errors, or, above all, imperfect (e.g. truncated, incomplete); therefore, inspection-based degradation prognosis based on SHM data have emerged recently [111]. SHM data, compared to NDT, are more abundant and comes from different sources allowing fusion of information to conduct a more comprehensive damage diagnosis; however, data encapsulate more noise and may also be distant from the monitored real variables. Regarding the **prognosis approaches**, mainly four classes may be defined [111]: Physics-based approaches, aiming at modelling the degradation process by understanding the mechanism behind it; ii) Data-driven models, which leverage statistical principles and different kinds of data to detect also the variations within and between different degradation paths; iii) Knowledge-based models, which leverage a knowledge base (e.g. a set of rule) to infer particular assertions, these are typically used when the phenomenon is not characterisable through specific mathematical models given the real-world complexity; iv) Hybrid methods, which expect to combine multiple approaches. Data-driven methods encompass Hidden Markov Models and also ML approaches such as Regression models, Bayesian Networks, ANNs, SVMs, and Deep Learning methods. Similarly, Knowledge-based models also involve AI-based solutions such as Expert Systems.

In our understanding, SHM systems can be subdivided into two major classes [113]: vibration-based and vision-based. In both cases, ML and DL have found great applicability as such approaches can improve detection and estimation performances. Reference [114], recently performed an overview of ML- and DL-based solutions in the context of vibration-based SHM which leverages vibration responses of the monitored structure to assess the overall conditions of the structure. Typically, **accelerometers** are used to collect the vibration responses of the structure, then, algorithms are implemented to translate those responses into indices reflecting the presence of the damage. Notably, a limited set of accelerometers is sufficient, moreover, such approaches do not require knowing the position of the damage a-priori. As **ML-based models**, mostly ANNs (also supported by genetic algorithms) and SVMs are used in the literature to address these kinds of problems; ML involves feature selection/extraction and, in this case, mostly modal parameters (e.g. natural frequencies, damping ratios, mode shapes) are considered. Also in this case, ML approaches have some drawbacks: modal characteristics may reflect other kinds of variations besides the structural damages (e.g. temperature) and may also be poorly sensitive to certain types of damages; additionally, it is difficult to say whether a particular combination of fixed hand-crafted features (obtained for example by applying the PCA or Auto-regressive models) and classifiers may be suitable for any kind of structures and any kind of damages. On the other hand, autoencoders and CNNs were implemented as **DL-based models**; notably, 1D-CNNs (one-dimensional CNNs) showed state-of-the-art performances and computational advantages, especially compared to traditional CNNs.

Reference [112] also proposed a systematic review on SHM applications but focusing mostly on Deep Learning approaches, specifically CNNs, and vision-based approaches. In our understanding, this choice was made basing on three factors: i) **non-contact sensors** (e.g. cameras or UAVs equipped with cameras) are easier to deploy, less labour-intensive, and more cost-effective; ii) traditional image processing techniques (e.g. Canny filter, Sobel edge detector, template matching) are often prone to be affected by environmental noise such as light, weather, shade, and occlusion; iii) ML-based approaches relies too much on feature extraction and may not be so suitable to assess full-scale structures such as buildings, bridges, and pipelines, although they work properly with small anomaly datasets. Topics including bridge health monitoring, pavements health monitoring, underground structures inspection, building condition assessment, multi-class structural monitoring, and large-scale structures inspection were addressed. It turned out that, in the context of vision-based applications, DL-based classification, detection, and semantic segmentation approaches (e.g. by applying fully convolutional networks - FCNs) were implemented and state-of-the-art CNN architectures including ResNet, AlexNet, ZF-net, GoogLeNet, VGG, Faster R-CNN, and YOLO were widely adopted. In different cases, also Transfer Learning approaches were adopted (e.g. by exploiting the ImageNet dataset for the architectures' pre-training). However, there is no shortage of drawbacks also in applying DL techniques, for example: in analysing tunnels' linings, a combination of CNNs and unsupervised clustering may be necessary to refine crack regions from noisy images collected under inadequate lighting conditions; in the context of pavements cracks detection, pre-processing techniques such as bilateral filtering and adaptive thresholding may be useful to deal with noise and complicated cracks; also, for multi-class structural monitoring, deeper architecture are required to classify various components and data labelling as crucial as time-consuming. Lastly, it is worth mentioning that *UAVs have already been widely deployed, in combination with Deep Learning, for vison-based SHM* [115–118].

6. Transferability Analysis

In this chapter, we leverage the knowledge acquired during the research activities conducted in the context of both WP1 and this document to delineate some promising transferability directions. Therefore, we first make a summary of the relevant railway problems emerged from WP1, specifically deliverable D1.3 [119] (Section 6.1); after, we establish transferability criteria (Section 6.2); then, we summarise the main AI-based applications we found in transport and non-transport sectors (Section 6.3); finally, we perform an analysis to provide possible transferability directions by crossing the information coming from the WP1 and the above chapters (4 and 5) on the bases of the individuated transferability criteria (Section 6.4).

6.1. Relevant Railway Problems

In deliverable D1.3 [119], we recognised the main relevant railway problems for which AI-based solutions have been or could be provided to improve maintenance and inspection activities. These problems were identified by merging information coming from the literature, the analysis of Shift2Rail projects, the advisory board, and a survey involving different research centres and enterprises. Figure 6.1 shows the subset of the railway problems falling in the context of maintenance. It is worth noting that "Predictive maintenance scheduling and planning" is related to both maintenance and traffic planning.

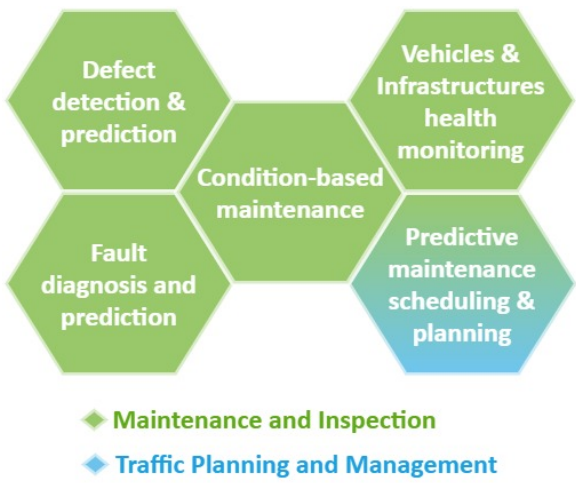

Fig. 6.1. Railway problems for AI application in WP3 (excerpt from D1.3 [119])

According to the Survey on Challenges and State-of-Practice (SoP) of Artificial Intelligence in railways conducted involving the railway stakeholders, addressing these problems using AI-based approaches the following major obstacles are to be expected:

- Safety, dependability and trustworthiness concerns;
- Lack of proper datasets for training the AI models;
- Lack of specific standards and regulations.

In the view of these indications and of the review work conducted in the first phase of the project, the application areas in the maintenance and inspection subdomain, as they have been identified in D1.3, include:

- Defect detection and prediction of different assets including rail tracks, infrastructures (e.g. bridges, tunnels), the pantograph and catenary system, and rolling stocks (e.g. car-bodies, bogies);
- Fault diagnosis and prediction for systems such as railway turnouts, track circuits, and wayside and on-board equipment;
- Condition-based, data-driven maintenance and health monitoring for different assets and systems as those listed above and other scenarios such as level crossings;
- Scheduling and planning of maintenance activities in a predictive manner also to optimally plan and manage the railway traffic.

However, these application areas were proposed based on the results of the activities performed in WP1, which aims to identify the potential of AI techniques within each railway subdomain. It effectively shows that a significant advancement has occurred in terms of AI approaches within the railway maintenance and inspection subdomain, especially in the areas mentioned above. Here, we enlarge our scope to perform a structured transferability analysis that is not limited to the railway industry but extends investigating and learning from other transport and non-transport sectors. Also, we are interested in understanding how technologies such as *IoT, Cloud Computing, Digital Twins, and Drones* can be exploited to improve railway maintenance applications. Therefore, in Section 6.4 we have outlined some possible transferability directions oriented to:

- *Assets defect and faults detection and prediction*. With the term “assets” we mean the set of infrastructures and physical systems composing a specific sector, directly related to train movements. In the context of the railways, the assets include rail tracks, catenary systems, level crossings, and all their components (e.g. turnouts, catenary support devices).
- *Vehicle Health Monitoring (VHM)*, including also defects and faults detection and prediction for vehicles components. In the context of railways, the term “vehicle”, represents powered (e.g. locomotives) or non-powered (e.g. wagons or carriages) moving units. Railway vehicles, including at least 1 powered and one or more non-powered, are connected together to become trains. Generally, all types of railway vehicles are composed of the following five basic parts: i) Car body, i.e. the structure for accommodating the physical cargo or passengers; ii) Running gear (or more commonly known as “bogie”), which is an independent part distinguished with railroad car); iii) Breaking device, including air break piping system and hand brake device; iv) Connecting and buffering devices, including different types of couplers and buffer discs; v) Vehicle internal equipment (e.g. electrical, water supply, heating, ventilation).
- *Structural Healt Monitoring (SHM)*, including also defects and faults detection and prediction for fixed structures in proximity of and supporting tracks (i.e. buildings made of concrete or other building materials). In this document, we are mostly interested in AI applications assessing tunnels and bridges health monitoring. We will refer to these structures as “fixed infrastructure supporting tracks”.
- *Cybersecurity applications*, a possible cyber attack can be active or passive. Where an ”active attack” means to alter system resources or affect their operations, while a ”passive attack” attempts to learn or make use/profits of information from the system but does not affect system resources. Different cyber-threats have increased the vulnerability of essential railway system even the critical railway infrastructure such as

signalling systems. From one hand, attacks becoming ever-more sophisticated, on the other, the potential damage that can result in financial loss and lives is growing. In this document, we specifically focus on providing a systematic framework to address cybersecurity challenges.

For the sake of knowledge, there may be cases in which rolling stock are equipped with sensors (e.g. cameras) to monitor, for example, rails (e.g. [120, 121]) or catenaries (e.g. [122, 123]), or vice-versa, vehicles components may be monitored by exploiting sensors installed on the trackside (e.g. [124, 125]). Hence, the subdivision reported above must be intended as a classification based on the purpose of the AI application (e.g. oriented to VHM by leveraging data coming from on-board or trackside sensors, or even both).

6.2. Transferability framework

Transferability refers to the possibility of transferring the results or findings of research from one domain (*source*) (e.g., automotive), to another domain (*target*) (e.g., railways). According to [1], transferability primarily involves the perception of who is interested in assessing the applicability of the research findings or technology that can be of potential use. The factors affecting this perception are based both on general considerations, i.e. *dimensions*, that are applicable across all railway subdomains, and domain-based concerns, i.e., *criteria*, which may vary according to the specific subdomain. Therefore, in this section, we introduce a **framework for transferability** to perform a structured transferability analysis of AI applications[1] from other sectors to railways by setting general *dimensions*, as in Deliverable D2.1 [126] and D4.1, and their derived *criteria*.

Transferability dimensions and related criteria have been defined by considering: a) the outcome of the DISCOVER[2] phase, which provides guidelines from the relevant stakeholders and from the analysis of the railway problems related to maintenance and inspection; b) the transferability analyses conducted in other sectors (e.g. [1], [2]). Although these studies are tailored to other scientific areas and other objectives, they provide some general indications. Also, we focus on scientific and technical aspects while social, political, and legal dimensions are not considered at this analysis. The order used to list transferability dimensions and criteria is not random. Instead, they are sorted in descending order according to their importance for the realisability and purpose of transferability. Note that the order may change for different domains/contexts.

Table 6.1 shows the definitions of the transferability dimensions we have adopted including **congruence, significance, similarity, maturity** and **implementability**. The corresponding transferability criteria are defined in Table 6.2.

Table 6.3 shows a Transferability Table (TTable) combining dimensions and criteria for a *transferability analysis*. The five levels (Very High, High, Medium, Low, and Very Low) specify *to what extent the transferability criteria are met* by a particular AI application, i.e. they indicate the perceived status of the AI application that is intended to be transferred. According to the specific dimension, levels may have different specific meaning; however, in general, the level "Very High" indicates that the application is easily transferable from a given

[1] In this document, we refer to AI-based methodologies, approaches, methods, techniques, and technologies as *AI applications*

[2] The RAILS project includes three phases: DISCOVER (including WP1), ASSESS (including WP2, WP3, and WP4), and LEARN (including WP5)

Table 6.1: Transferability Dimensions

Dimension	***Description***
Congruence	the adherence between the AI application intended to be transferred in the source domain and its counterpart in the target domain.
Significance	the benefits that the AI application may bring in the target domain if successfully transferred, regardless of its maturity.
Similarity	the similarities between the specific goal of the AI application in the source and target domains and between the characteristics of the two domains.
Maturity	the advancement of the AI application in the target domain.
Implementability	the effort and costs needed to implement the AI application in the target domain considering the required technologies, skills and the possibility to maintain the application over time.

Table 6.2: Transferability Criteria

Dimension	Criterion	Description	Example
Congruence	*mission/aim/scope*	the adherence of the AI application that is intended to be transferred to the mission, aims, and scope in the target domain.	Two surface defect detection applications have the same mission/aim/scope in both the source and target domain, even though their specific implementation may vary depending on the domain characteristics.
	previous experience	the previous experience, i.e. the research/developing status of an AI application in the source domain.	?
	failure severity	the gap that exists in terms of unpleasant consequences between a valuation error in the source domain and a valuation error in the target domain.	A valuation error in the quality assessment phase of a consumer product (e.g. a textile product) leads to slighter consequences than an incorrect quality assessment of a component that will be used in transport systems, where human lives may depend on it.
Significance	*potential effectiveness*	how much effective could be the AI application if successfully transferred.	?
	impact	the positive impacts that the AI application would have in the target domain in successfully transferred.	?
Similarity	*goal*	the similarities between the specific goal of the AI application in the source and target domain as, even though they may have the same mission/aim/scope in both the domains, their specific implementation may vary depending on the specific goal.	Considering two AI applications, one aiming at detecting defects in textile products and the other aiming at detecting defects in train bogies. The mission/aim/sope is mostly the same, i.e. defect detection, but the two specific goals are quite different. For instance, the former may be oriented to detect only scratches, the latter to detect also missing components.
	domain characteristics	how different are the target and source domains in terms of their peculiarities.	If an AI application performs properly in the source domain, it may not work as well in the target one, given the conformation of the domain itself. There may also be inconsistencies in terms of safety requirements and regulations.
Maturity	*AI application*	the grade of maturity that the AI application has achieved in the target domain in terms of its research/developing status.	?
	automation	the grade of automation that can be associated to an AI application in the source domain.	?
Implementability	*technology*	whether the technology in the target domain is mature enough to accommodate the AI application or further improvement are needed.	?
	sustainability (costs and effort)	the costs and effort needed to maintain the transferred AI application in the target domain over time.	?

point of view (i.e. criterion); differently, the level "Very Low" indicates that the transfer require a huge effort. For example, a "Very High" mission/aim/scope indicates that the application intended to transfer is highly suitable for our purposes; otherwise, if evaluated as "Very Low", it means that we can only use that application as a starting point, and significant adjustments would be needed for its effective integration to our purposes. Therefore, cells contain checkmarks (✓) indicating the perceived level of the corresponding criterion (there will be a single checkmark within each row). The colours have been introduced to visually support the TTable: the more checkmarks are in the "green area", the more the AI application is suitable for transferring. Note that the tables do not assess the level of progress of the considered source sectors, but its suitability to railways. Moreover, the assessment of these levels is subjective (as in many other qualitative analysis) and a way to establish the thresholds for

Table 6.3: Transferability Table (TTable)

Dimension	Criterion	Evaluation: *Very High*	*High*	*Medium*	*Low*	*Very Low*
Congruence	*mission/aim/scope* *previous experience* *failure severity*					
Significance	*potential effectiveness* *impact*					
Similarity	*goal* *domain characteristics*					
Maturity	*AI application* *automation*					
Implementability	*technology* *sustainability* *(costs and effort)*					

Source Domain(s): [domain_1], [domain_2]

their evaluation must be provided case by case.

To summarise, the goal of the TTable is to provide guidelines for the transferability of a given AI application to the railway sector for a specific objective[3]: it says whether it makes sense, and to what extent, to take further steps in that direction. Notably, for a given AI application identified within a specific sector, there may be similar counterparts in other domains. Therefore, in Section 6.3, we summarised the possible applications that may be of interest to transfer. Then, in Section 6.4, we adopted the following methodology to select the most suitable AI application to transfer to the railway: i) we considered similar solutions coming from other sectors (if multiple); ii) in case of multiple hints from multiple source domains, we selected the most suitable one to be transferred; and lastly, iii) we provided a TTable and related explanation for the AI application identified in the previous point (if necessary). We adopted this reasoning for each different AI-based solution we found promising to transfer in Section 6.3.

6.3. Synthesis of AI applications in transport and non-transport sectors

In this section, the relevant promising applications discussed in Chapters 4 and 5 are reported. They refer to AI-based solutions that have been adopted in both transport (Avionics, Automotive, and Maritime) and non-transport (Manufacturing, Machinery, and Critical Infrastructures) sectors. Additionally, such AI approaches have been clustered according to the categories identified in Section 6.1. The aim is to point to the more relevant topics discussed in the previous part of the document.

Assets defect and faults detection and prediction

In the literature, there is a plenty of studies aiming at assessing/predicting rail tracks and catenary systems defects/faults by exploiting AI-based approaches. Therefore, we can state that, at least from an academic point of view, the rail sector has achieved an advanced grade of development; hence, a transferability analysis for **AI-based machine fault diagnosis or**

[3]This represents a first step towards the definition of a transferability methodology that needs to: i) be further developed in the next project tasks, perhaps supported by discussions with the Advisory Board and future workshops; ii) be integrated with additional studies or tools (e.g. proper checklists)

surface defect detection applications (for example, from manufacturing, Section 5.1) may be superfluous. Differently, the **AI-based additive manufacturing and geometric error compensation applications** may be interesting when considering production aspects also in railways. Actually, for example, attempts have already been performed within the rail sector towards AI-based quality assessment of rails (e.g. [127]) but, to the best of our knowledge, it is still at an early stage. Despite being very interesting, we will not address "production" aspects within this document, however, it is worth mentioning that the railways could borrow solutions from manufacturing to cope with some of these aspects. Considering the technologies, first tryouts towards **Drone-based image acquisition for assets monitoring** have been performed in the railways regarding rail tracks defects (e.g. [128]) and catenary systems defects (e.g. [129, 130]). However, drones are still "human-driven", therefore, as possible future applications, such as the AI-based autonomous drones path planning (reviewed in D2.1 [126]) may be combined with AI-based assets monitoring to achieve a fully automated inspection. Also, within manufacturing and machinery, some applications with high grade of development have been found regarding **AI-aided fault diagnosis and prognosis through Digital Twins and IoT**; it would be interesting to investigate these applications to cope with, for instance, rail track moving components (e.g. turnouts) or level crossings. However, in the latter case, as suggested by the Advisory Board, the idea could be to adopt non-intrusive sensors (e.g. cameras and microphones) to assess level crossing status and estimate their Remaining Useful Life (RUL); particularly, we would be more oriented to **Motion-based RUL estimation through non-intrusive devices**.

Vehicle Health Monitoring (VHM)

With the development of monitoring techniques, nowadays the research focus of vehicle health surveillance transitions from condition monitoring to health management. Existing applications have generally focused on fault disgnosis of a certain part (e.g. an aero-engine and an airborne electronic equipment), as seen in Section 4.1. However, the current findings of VHM in aviation field is that these applications have been far from satisfying the practical needs of aeroplane vehicle safety. The reason behind it can be explained from two different perspectives. First, hundreds/thousands of air planes need to be managed simultaneously, which means ever-growing monitoring data would be generated and this requires researchers to figure out how effectively implement integrated management on such a complex transport system. Second, it is also essential to improve reliability of a single airplane by judging the health status of this whole airplane. For these reasons, in recent years, many airline companies/aviation safety institutions have put great efforts to develop a unified method of **Integrated Vehicle Health Management (IVHM)**, and the most famous project is the one proposed by NASA (2008-2012)[131]. Similarly, such application approach can be transferred into the railway vehicle maintenence applications. From the literature review of D1.2 [126], few attempts on performing integrated/systematic vehicle health management framework within the rail sector have been found, but this application is still in early stages of development. It appears that some new concepts, such as Prognosis and Health Management (PHM), Integrated System Health Management (ISHM), and Health and Usage Monitoring System (HUMS) has emerged in railway transport field. However, these ideas seem not to have been greatly implemented into railway vehicle condition surveillance. One example is, based on CBM, the US Department of Defence proposed CBM plus (CSM+) that integrates CBM concepts into the conventional vehicle reliability management, such as **CBM-based automatic maintenence and repair for overall planning**, **design of equipment health management**, **CBM-based on-board equipment status monitoring**, and **maintenance decision supporter and useful life prediction**. All these concepts are promising attempts of exploring deeper on this direction however they still need to be properly implemented and evaluated in the future work.

Structural Health Monitoring (SHM)

As for assets defect/faults detection and prediction, in the literature, there are different studies assessing defect detection for *fixed infrastructures supporting tracks* (i.e. bridges and tunnels) by exploiting AI approaches. Also, analyses on bridge and tunnels health monitoring have already been carried out within the S2R IN2TRACK [132] and IN2TRACK2 [133] projects: automated methods have been presented for inspection activities and also Building Information Modelling (BIM) methodologies have been discussed for both bridges and tunnels maintenance. Similarly, different AI applications for SHM have been found in the context of the analysis conducted in Section 5.3.2, where different approaches, both vibration- and vision- based, have been reported. Hence, we could say that AI-based applications oriented to crack detection or structure health monitoring have achieved substantial results.

In the context of railways, although tunnels introduce some complexities (e.g. uneven illumination, image noise), AI applications have shown great potentials to identify surface defects; differently, to the best of our knowledge, bridges introduce more practical challenges, mainly related to safety during data acquisition. Therefore, to understand to what extent it is possible to automatise this acquisition process, in this document, we focus on **Autonomous drone aided AI-based rail bridges health monitoring**. Potentials of using drones (or UAVs) have been analysed to easily monitor inaccessible bridge element while avoiding traffic disruption and workers safety issues [134]. Actually, attempts have also been performed towards the implementation of autonomous drones and AI-based solutions oriented to SHM [115, 117], some of which particularly focus on bridge condition assessment [118]. Notably, reference [118] proposed a framework to autonomously acquire image data of bridges using UAVs aiming at producing a 3D model of the structure and performing anomaly detection for structural condition assessment; additionally, the authors considered a rail bridge as case study.

Cybersecurity applications

Although centralised data management has benefits of data integration and management, it may lead to critical security issues and privacy problems. The transport authority institutions can hardly trustfully store their data, particularly the confidential data, in a data center they cannot fully control. Also, by the distributed mode, institutional stored data distribute in their own data clusters. Although they can control security strategy, there exist bug challenge for data integration. Operating individual devices using IoT in aerospace segment, has to consider massive of challenges in aircraft type certificate. Which means that devices within the aircraft have to be certified under safety regulations, typically following the DO-178 standard for software, and DO-274 for hardware [135]. These considerations give a more complex and strict requirement for developing IoT applications in aviation even the whole transport sector compared to the similar consuming scenarios. In addition, it is required to ensure that safety critical flight/navigation systems or networks are not connected to devices through internet to protect them from malicious cyber attacks. The availability of bandwidth provides an effective opportunity to be implemented for avoiding the potential intrusion attacks [136]. Particularly, the open access data of railway transport sector shows that many railway organisations focus on detecting security threats with less emphasis on forecasting them. To get fully prepared in advance for cyber attacks, it is essential that both Information and Communication Technology (ICT) and Operational Technology (OT) are simultaneously updated to enable security analytic approach. The current standards and guidelines available in railways (e.g. AS-7770-Rail Cyber Security, APTA SS-CCS-004-16 [137]), are proprietary (i.e. either organisations-specific or country-specific). These proprietary standards are weak at providing a holistic approach to enable scalability, orchestration, adaptability, and agility for railway stakeholders. There is a need to develop a generic **cybersecurity framework for digitalised railways** to facilitate proactive cybersecurity and threat intelligence sharing within the railways.

6.4. Directions for Transferability

The maintenance and inspection subdomain is one of the most investigated within the rail sector, therefore, finding completely new applications to transferring concepts from other domains is not a straightforward task. In the following, we perform the transferability analysis and provide TTables for some of the most promising applications, taking also into account those that could be helpful to cope with some of the scenarios we would like to investigate in the near future.

6.4.1. AI-aided fault diagnosis and prognosis through Digital Twins and IoT

Here we particularly explore the possibilities of Digital Twin (DT) and Internet of Things (IoT) concepts for diagnosis and prognosis. A Digital Twin (DT) is a virtual system that evolves with its physical counterpart thanks to IoT sensors. Therefore, DTs are powerful means to monitor physical systems in real-time which open for safer failure prediction and fault detection/diagnosis as it is possible to evaluate the response of a physical system by stimulating its digital counterpart [99] without affecting the system operability.

Given their potentials, Digital Twins have been investigated in different scenarios. In Avionics (as described in section 4.1), they have been adopted to mitigate degradation by activating self-healing mechanisms or by recommending changes in the mission profile to decrease loading, or to reduce the downtime for plane engines and other essential supportive systems. Additionally, in the Manufacturing (section 5.1) sector, they have been exploited to cope with manufacturing tools Remaining Useful Life (RUL) estimation and to optimise the production process. However, as manufacturing tools are actually machinery systems, we could merge these solutions with those identified in the Machinery field (section 5.2), where they have been proposed to solve similar problems (i.e. systems RUL estimation). It is worth noting that Digital Twins have also been investigated to cope with tasks that go beyond maintenance purposes including dependability improvement of autonomous driving [138]; however, these applications are out of the scope of this report.

Advancements towards the adoption of Digital Twins have already been done also in the railways. For instance, the S2R project LOCATE is heading towards the realisation of train bogie digital twin. Similarly, other S2R projects have conducted analyses to assess the potential of digital twins for control command and signalling (X2Rail project series), rolling stock (Pivot and TAURO), infrastructures (IN2TACK I and II), and stations (IN2STEMPO)

[52, 139].

In these contexts, IoT sensors are considered enabling technologies, however, their introduction may be very challenging in some scenarios. First, rails span over hundreds of kilometres, therefore it would not be feasible to install a disproportionate amount of sensors along with them. Second, when it comes to safety-critical systems, the introduction of new components may lead to re-approval processes that could be very expensive and time-consuming. Indeed, we must take into consideration that new systems, deployed in the last years, are most likely already equipped with a set of sensors that may facilitate the realisation of a digital counterpart, but this may not be true for the oldest ones, deployed thirty or even fifty years ago, which are still operating and require, for clear reasons of wear, to be maintained and inspect more frequently. Therefore, in addition to the study carried out in this report, cost analyses will be needed to understand to what extent the “digitalization” of a component is advantageous.

By narrowing the scope, we identified a specific scenario in which AI-aided analyses based on digital twins may be highly advantageous. Despite the fact that our primary purpose is to assess the Level Crossings (LC) health status by exploiting non-intrusive approaches not to run into re-approval issues, it may be possible to exploit Digital Twins and AI if LCs are already equipped with the required IoT sensors.

Considering the **AI-aided Level Crossings Prognosis based on Digital Twins and IoT** application, results obtained within the manufacturing and machinery sectors seem to be more suitable in respect to other sectors. Even though there have been proposed complex digital twins for, e.g., aircraft engines [140], here we are interested in evaluating a system that performs always the same actions with a limited decision-making margin. Specifically, we are interested in monitoring the level crossings and understanding their (failure) state, and not in making them intelligent capable of automatically adapting to the environment. Therefore, the TTable 6.4 shows the evaluation of the transferability criteria by considering the results that have been achieved within the machinery sector (e.g. [141, 142]). Analysing the distribution of the checkmarks, from a conceptual point of view, solutions found within the machinery sector shows a medium to high level of advancement, and may have a great impact in the rail sector. However, Digital Twin-based solutions are still at a very early stage in the railways: in our perception, a sufficient maturity level of the *AI application* specific for level crossing has yet to be conceived. Advancements from both the technological and research perspective are required to accommodate such kind of applications. We describe each dimension and criterion in the following.

Congruence: the *mission/aim/scope* is practically the same in all the considered sectors, i.e. fault analysis and RUL estimation. The *previous experience* is quite exhaustive (at least theoretically), despite the fact that not always DTs have been combined with AI; often, they have been employed for monitoring activities only. Differently, the *failure severity* differs significantly: in manufacturing, a failure may lead to service disruption; in machinery (depending on the application field), a failure may lead to unpleasant consequences (including injuries); in the railways, considering the LC as a safety-critical system, a malfunctioning may cause serious accidents (including fatalities). Notably, fatalities from level crossing accidents account for about 30% of all the fatalities registered in railways scenarios [143].

Significance: the DTs will bring different advantages from an online and remote monitoring to a safer injection analysis of LCs (i.e. to safely study the response of the system

Table 6.4: TTable: AI-aided Level Crossings Prognosis based on Digital Twins and IoT

Dimension	Criterion	Evaluation				
		Very High	*High*	*Medium*	*Low*	*Very Low*
Congruence	*mission/aim/scope*	✓				
	previous experience		✓			
	failure severity			✓		
Significance	*potential effectiveness*		✓			
	impact	✓				
Similarity	*goal*		✓			
	domain characteristics			✓		
Maturity	*AI application*				✓	
	automation			✓		
Implementability	*technology*			✓		
	sustainability (costs and effort)			✓		

Source Domain: Machinery

given some inputs, malicious or not). Therefore, the *impact* would be very significant. Somewhat differently, the *potential effectiveness* depends on both other possible AI applications that may be exploited to achieve the same purpose (e.g. Motion-based RUL estimation through non-intrusive devices, section 6.4.4) and some issues as described below.

Similarity: the *goal* between the source (manufacturing and machinery) and the target (rail) domains is mostly the same: RUL estimation or fault analysis of mechanical/moving components. However, there are some differences when it comes to the *domain characteristics*. While machinery systems may also work in isolation, Railways include many “agents” (e.g. pedestrians, cars, trains), especially in the level crossing environment. This results in a very complex scenario where a system failure may involve different parties, hence, systems must be compliant with strict regulations. Therefore, the addition of new sensors may be challenging as this could lead to expensive and time-consuming re-approval processes. However, it is also possible to investigate how digital twins have been conceptually integrated in other transport sectors (e.g. [20]) to possibly understand how standards and safety regulations could be met.

Maturity: DTs have been already investigated within the rail sector, however their practical *application*, specifically combined with AI, seems to be still at an early stage; as well as, maintenance and inspection activities at level crossings seem to be not completely *automated* yet.

Implementability: from the *technological* point of view, we have already stated that the newest LCs may be equipped with a set of adequate sensors allowing the realisation of DTs with limited effort. Instead, there may be thousands of (dated) level crossings that would need some upgrades in order to build digital twins. Also, from the *sustainability* perspective, it would not be so straightforward to maintain such an application, not so much for aspects related to DT or AI, as for the fact that sensors may require maintenance activities in turn.

To conclude, Digital Twins of level crossings tend to represent a suitable solution for their condition monitoring. However, if the LCs are not already equipped with appropriate sensors, it may be quite challenging as we could run into re-approval processes. Therefore, in Section 6.4.4, we present a new possible solution (based on transferability) that may allow a condition monitoring based on non-intrusive sensors and can be applicable to both old and new LCs.

6.4.2. AI-aided asset and bridge health monitoring based on autonomous UAV

Based on review of UAVs [126], there has been a great advancement in AI-aided autonomous flight and path planning in recent years. However, when combining autonomous UAVs with SHM applications, we were able to find only a limited amount of approaches, mainly within Critical Infrastructure (CI) applications (Section 5.3.2). These CI applications exploited autonomous UAVs (i.e. drones capable of performing a fully automated data acquisition) for data collection of structures. Notably, AI applications for asset monitoring based on images captured by UAVs have already been investigated within the railways (e.g. [128, 129]), however, we did not find hints for data collection based on **autonomous** drones.

In the context of **AI-aided asset and bridge health monitoring based on autonomous UAV**, the transferability analysis focuses on the observations from Critical Infrastructure SHM.

Table 6.5: TTable: AI-aided asset and bridge health monitoring based on autonomous UAV

Dimension	Criterion	Evaluation: *Very High*	*High*	*Medium*	*Low*	*Very Low*
Congruence	*mission/aim/scope*	✓				
	previous experience			✓		
	failure severity		✓			
Significance	*potential effectiveness*	✓				
	impact	✓				
Similarity	*goal*		✓*	✓**		
	domain characteristics			✓		
Maturity	*AI application*		✓			
	automation		✓			
Implementability	*technology*			✓		
	sustainability (costs and effort)		✓			

Source Domain: Critical Infrastructures - Structural Health Monitoring.
*bridge health monitoring; **asset health monitoring

Table 6.5 shows the evaluation of the transferability criteria for **AI-aided asset and bridge health monitoring based on autonomous UAV**. Notably, most of the checkmarks fall into the “green area”, except for those related to the *previous experience*, *goal* (in the case of asset monitoring), *domain characteristics*, and *technology* criteria, which we have perceived at a “Medium” level. Specifically, we describe each dimension and criterion in the following.

Congruence. The main *mission/aim/scope*, i.e. AI- and image-based defect detection, is quite general and widely addressed in almost all the fields, however, the *previous experience* tailored on the combination of the aforementioned solutions seems not to be very advanced in CI as in other sectors. Regarding *failure severity*, the rail sector may present some additional challenging aspects related to the failure of both the AI application and the hardware needed: following a failure, the inspection drone may land/fall on the rail tracks, becoming an obstacle and thus impacting railway traffic.

Significance. If successfully transferred, this application may lead to several benefits including an increment in workers safety, time-saving, disruption reduction, and real-time health monitoring. However, additional considerations are needed, as stated in the following point.

Similarity. The specific *goal* depends on the final application we are considering: in case of rail track and catenary inspection, applications borrowed from CI SHM may require a significant tuning, as these components are quite different from concrete buildings; however, it would be possible to exploit what has already been carried out within the rail sector in the context of asset health monitoring to close this gap. Otherwise, when addressing rail bridges, there would not be such a big difference, even though that rail bridges may be equipped with some supports that differs from those involved in buildings or bridges related to other sectors. Differently, we have some great differences regarding the *domain characteristics*. Specifically, there are some **regulatory issues** as the practical idea is to introduce autonomous entities to inspect assets and structures without traffic disruption. Here we have two possible scenarios: a visionary one, that expects drones operating fully autonomously, and a more affordable one, that expects drones to operate in a semi-autonomous fashion. In the first scenario, UAVs must coherently coexist with the current rail systems, rolling stock included, which means that they should be somehow incorporated within the communication system to dynamically recognise when it is possible to "safely" inspect the assets (i.e. when no train traffic is passing). The latter scenario expects workers to be an integral part of the inspection activity by supervising and manoeuvring the drone operations, even if the UAV is supported by obstacle detection or "return to home" functionalities (in case of connection lost or other kinds of disruptions). However, in both cases, **safety** concerns still exist. In case of failure, the UAV might fall on the railways and become an obstacle for the running train (as already stated) but, in the worst case, considering the possible high speed of the train, the drone might also became a sort of projectile and affect the safety of drivers and passengers. Notably, by flying drones to the side of the railways (and not exactly above them), this risk may be reduced.

Maturity. In general, AI-aided health assessment has achieved optimal results in the rail sector, while autonomous UAV for data acquisition have not been investigated much. Even tohough autonomous AI-based UAVs have progressed flourishingly in the last years, there is a need for more fully exploitable proofs-of-concept regarding their conjunction to achieve a proper level of maturity of the *AI application*. Concerning the grade of *automation*, more and more studies are reporting a great advancement towards data-driven and semi (or full) autonomous inspection methods, which is welcome for rail applications.

Implementability. Unfortunately, a huge amount of effort would be needed to develop such an application tailored to the rail assets monitoring, also taking into account the domain characteristics and safety concerns. Additionally, on-field testing will be mandatory. However, beyond the research and testing costs, we estimate that no expensive hardware is required, even though some *technical* issues related to the kind and weight of the sensors a drone can carry (e.g. cameras or LiDAR) and the flight height/angle arise. In the context of maintenance, high quality data are required to effectively detect defects, hence, a suitable combination between sensors, flight height, flight speed, collection FPS rate, and acquisition angle must be identified; taking also into account that the catenary system are characterised by high voltage which may interfere with the drones operation. Nevertheless, once developed and successfully transferred, the whole application (software and hardware) may not need challenging adjustments over time.

To conclude, the checkmarks distribution in TTable 6.5 and the above analysis indicate that the proposed AI application will have a substantial impact and bring multiple benefits to the railways. However, further research activities are needed to compensate the experience level and, in the case of asset monitoring, alienate the goals of the application in source and target domains. Lastly, a detailed and careful analysis must be performed to understand how (and if) autonomous UAVs may coexist with the current regulations.

6.4.3. Vehicle Health Evaluation based on Big data management (IoT-based) and Cloud Computing

The Big data-based management platform may be combined with Cloud Computing to realise a more effective data transit manner in the domain of **Identification and storage of railway disruption logs**, which consists of

- standardisation of big data (all these maintenance big data are heterogeneous, standardisation can effectively improve usability of the data)
- Data sharing of railway data among the centralised or distributed data centres.Generally speaking, there are two modes in railway big data sharing platform. one is centralised mode that stores all railway data in a data centre and centrally manage the data sharing; another mode is to distribute stored data in data centres of different institutions and separately manage the data sharing.
- popular applications based on railway big data including: rail car fault disgnostic system, train vehicle fault prediction system, train vehicle maintenance decision system, and train vehicle health evaluation system.

According to these characteristics of hybrid Big Data-based and Cloud Computing platform, a clear trend can be identified: the research focus of Vehicle Health Evaluation in general transport field has gradually shitted from condition monitoring to the direction of comprehensive health management framework, especially in the domains of aerospace and automotive. Existing business solutions within the context of generalised VHM shows a great homogeneity of the application scenarios, which means the implemented applications may have largely focused on specific component/sub-system of the on-board equipment [144] (e.g. End of Life (EoL) estimation for fuel pump) rather than considering the solution beyond the scope of improving efficiency and reliability of automotive components. Although some attempts have been performed in the railway sectors, IoT-based Cloud Computing platforms are still at its very early stage compared to other transport domains. The original application was derived from aviation sector however latest studies started to investigated the possibility of implementing similar application in automotive domain. In the past few years, big data-driven Prognostics and Health Monitoring (PHM) framework based IoT has been greatly investigated on the tasks of monitoring Remaining Useful Lifetime (RUL) and condition value of critical system equipment (e.g. [144] and [145]). However, according to the survey about Vehicle Health Evaluation in the context of railways, there is a lack of a systematic framework of PHM to create more added value for the business/industrial purpose (e.g. [146]). It is shown that with the support of **IoT-based big data-driven cloud computing platform**, we have more interests to explore the transferability of **Integrated Vehicle Health Management system under the Internet of Railway-cars**.

Table 6.6 gives a straightforward illustration about how the pre-defined criteria apply for the transferability dimensions in terms of the Vehicle Health Evaluation based on Big data management (IoT-based) and Cloud Computing platform. Generally speaking, most of the checkmarks fall into the categories of ”Very High” and ”High”. Except for those measures for ”Similarity”, with the rating of ”Low” and ”Medium”, respectively. We describe each dimension with the following measures.

Table 6.6: TTable: Vehicle Health Evaluation based on Big data management (IoT-based) and Cloud Computing

		Evaluation				
Dimension	**Criterion**	*Very High*	*High*	*Medium*	*Low*	*Very Low*
Congruence	*mission/aim/scope*		✓			
	previous experience		✓			
	failure severity	✓				
Significance	*potential effectiveness*	✓				
	impact		✓			
Similarity	*goal*				✓	
	domain characteristics			✓		
Maturity	*AI application*		✓			
	automation	✓				
Implementability	*technology*		✓			
	sustainability (costs and effort)		✓			

Source Domain: Aviation - Vehicle Health Monitoring.

Congruence. The *mission/aim/scope* in the source domain, i.e. estimating End of Life (EoL) and Remaining Useful Lifetime (RUL), is quite general and widely discussed in the domain of aviation and automotive, and partly investigated in railway domains (e.g. bogie). Since the field of other transport domains hold a similar definition about the term ”vehicle”, and vehicle is the most significant participant in the transit activities, both *previous experience* and *failure severity* are deserved to be assigned with a ”high” or even ”very high” evaluation result — once there is a failure of VHM system or an incorrect estimation of time-to-failure, then the public accident caused by them will be tremendous.

Significance. Obviously, the successful implementation of integrated IoT and cloud computing platform may bring to us several benefits range from a dynamic car-to-car network to a more efficient high-performance remote computing hub for the real-time health condition monitoring data. This is why we evaluate the *potential effectiveness* and *impact* as ”very high” and ”high” respectively in this table.

Similarity. The specific *goal* in the source domain is greatly different with that of in target transferred domain. That is, originally the cyber-physical systems may only utilise embedded software and local-area internet of Things to predict the remianing useful performance over the life of the asset, which is quite different from what we expected in railway sector. In case of rail car and health condition inspection, applications require a significant amount of real-time condition data from multiple kinds of sensors distributed over the whole vehicle instead of a single component, and cloud computing centre iteratively absorb these data in such that health management models can be collaboratively trained by different train vehicles. Not surprisingly, we have great differences regarding the *domain characteristics*. Specifically, there are some **regulation**

protocols issues as the applications in the source domain and target domain observe totally different regulation agreements, especially the domain of private transport (i.e. automotive) and public transport (i.e. national railway system). There are very different tolerances regarding the acquisition resource requirement, data openness and processing requirements on the vehicle condition information. The practical idea is to introduce autonomous entities to inspect assets and structures without traffic disruption.

Maturity. In general, Vehicle Health Evaluation based on Big data management (IoT-based) and Cloud Computing in railway domain have been partly investigated, even the concept of Integrated Vehicle Health Moniting (IVHM) has been proposed for a long time in the neighbour transport sector (e.g. aviation). There is a significant need for more fully exploitable regarding the systematic VHM framework to improve the degree of maturity for the applied *AI application*. As for the measure of *automation*, the Internet of Vehicles (IoV) based on the centralised cloud computing hub is regarded as one of the most automated applications in the general transport sector.

Implementability. Compared to other potential applications, the successful transferability may require a huge amount of effort to install massive number of rail vehicle health monitoring sensors. Additionally, a independent operated cloud computing infrastructure need to be maintained with the similar significance level of on-board IoV internet. Such process may adopt a series of novel technologies including wireless transmission protocols, self-organising Zigbee network, and edge computing, etc.

In conclusion, the hybrid framework integrating Big-Data techniques and Cloud Computing platform not only enables heterogeneous data resources to be incorporated for an universal usage, but also addresses the challenges brought by decentralised sensors/computing hubs. This is a revolutionary innovation that could perform VHM over the whole vehicle instead of a single component.

6.4.4. Motion-based RUL estimation through non-intrusive sensors

We found only a limited number of contributions in the literature assessing RUL estimation through image data, as presented in Section 5. Typically, RUL estimation is performed leveraging signal (e.g. current, vibration) as their variability over time describes, in certain way, how the system evolves. Therefore, the concept should remain the same also when considering images (or data coming from contactless sensors), i.e. the degradation images stream should intuitively be modelled as a spatiotemporal process [147]. Reference [147] proposed two models, a CNN-LSTM-based model and an autoencoder-based one, to cope with bearings time-to-failure (TTF) estimation through degradation images. Similarly, reference [148] proposed an approach based on CNN and LSTM to estimate the RUL of cutting wheels leveraging grey-scale images. Lastly, reference [149] performed machinery degradation condition estimation by leveraging CNN, LSTM, and degradation infrared image streams. However, our aim is to estimate the RUL of moving components by analysing how their motion path within adjacent video frames, therefor, in our understanding, the transferability can be only performed by levering the reasoning behind the adopted DL techniques, and how they were merged, but not the specific approach nor the data. Hence, our vision encompasses **estimating the RUL of moving objects**, i.e. the deterioration relies in the trajectory that the object traces and not on its degradation status captured by a single image.For example, in the context of level crossing, we would like to estimate the RUL of the gate arm, which is a moving object in the video stream; the faultiness is given by its movement (e.g. if it open/close smoothly or jerkily) and may not be related to the degraded wearing conditions of the object itself (e.g. scratches, dents).

TTable 6.7 reports the evaluation of the transferability criteria based on the aforementioned AI-based applications for image-based RUL estimation investigated within the machinery sector oriented to **Level Crossings AI-aided and motion-based RUL estimation leveraging video data**. Considering the checkmarks, both the criteria belonging to the *significance* dimensions are “Very high”, which means that such kind of application, if successfully developed, will bring huge benefits to the railways. Nevertheless, we did not find a fully compliant AI application in other sectors, indeed, the *mission/aim/scope*, *previous experience*, and *goal* criteria are set to “Medium” or “Low”. Lastly, the level of maturity of this *AI application* (i.e. AI-aided motion-based RUL estimation) is “Very Low” as the specific approach we are looking for is yet to be fully investigated even in other sectors. Dimensions and criteria are described below.

Table 6.7: TTable: Level Crossings AI-aided and motion-based RUL estimation leveraging video data

		Evaluation				
Dimension	**Criterion**	*Very High*	*High*	*Medium*	*Low*	*Very Low*
Congruence	*mission/aim/scope*			✓		
	previous experience				✓	
	failure severity				✓	
Significance	*potential effectiveness*	✓				
	impact	✓				
Similarity	*goal*				✓	
	domain characteristics			✓		
Maturity	*AI application*					✓
	automation			✓		
Implementability	*technology*		✓			
	sustainability (costs and effort)	✓				

Source Domain: Machinery

Congruence: As stated above, we are interested in evaluating the status of a moving object by considering its movement within adjacent frames. Therefore, the *mission/aim/scope* is highly different and we could consider what has been done in the machinery sector only from a theoretical perspective. Additionally, as also stated before, there is also a lack of *previous experience*. Lastly, the *failure severity* differs quite consistently: the railways encompasses different safety aspects, especially when considering safety-critical systems such as level crossings.

Significance: If successfully developed, the AI-aided motion-based RUL estimation would have great *effectiveness* and *impact* for two main reasons: i) it will not be necessary to equip the levels crossings with additional sensors (if not contemplated during the realisation phase of the system); ii) it would be possible to exploit the cameras already used for surveillance purposes at level crossings (where present). The latter point should be better investigated and discussed in the following RAILS project tasks.

Similarity: the *goals* of the source and target applications as the former estimates the RUL of static objects (in the sense that the position of the object does not change) within the images. The differences in *domain characteristics* between machinery and railways have been already emphasised in . However, since in this case no modification to the systems would be required, this application may be simpler to introduce in the railways from a technical perspective. At the same time, some effort will be needed to understand to what extent this solution can be trusted: a valuation error may lead to severe consequences.

Maturity: such kind of *AI application* is still at a very early stage in many sectors, and the railway is not an exception; as well as, maintenance and inspection activities at level crossings seem to be not completely *automated* yet.

Implementability: despite being challenging from a theoretical perspective, such an application will not involve specific *technology* requirements, beyond the a set of hardware capable of properly run AI-based applications. Indeed, surveillance cameras already installed at level crossings may be exploited to this aim. Therefore, the whole application (software and hardware) will also be easy to maintain over time as no many additional activities would be required.

Taking into account what has been done in the other sectors, we could only extract some general guidelines regarding the image-based RUL estimation, however, there is not an already developed (or fully understood) AI application that could be directly transferred. Conceptually, we can use the observations in the machinery sector as a good starting point, but the application we are looking for should be developed mostly from scratch.

6.4.5. Reducing malicious cyber attacks by using Cybersecurity Taxonomy Framework (CTF)

In the section 5.3, we pay our attention to investigating both cyber and physical infrastructure protection and maintenance. According to [150], the current trend of cyber-attack pattern can be attributed to higher maturity of attack tools and methods, increasing exposure, and multiple motivations of attackers. In the past, most of the attacks were conventional and the potential attackers are individuals or small group of hackers and the responding strategies are mostly passive defence or prognostic intervention. Nowadays, the significance of cybersecurity has received ever-growing attentions, which force us to investigate more effective techniques to protect the transport assets and devising creative solutions to mitigate risks. Specifically, we have also performed a small-scale review on how the applied AI-based solutions that greatly benefit the security domain in non-railway transport sectors (see section 6.3), and how the possible AI-aid solutions implemented in the non-transport sectors (see section 5.3.1). Given the findings, we can briefly summarise these applications into three categories: anomaly detection for vehicles, securing data link communications and security certifications [151].

However, the shifting towards a smarter paradigm based on artificial intelligence solutions has brought us another inevitable paradox [106]: the autonomous systems are becoming more dependable because of the introduction of higher intelligence while this can also reduce the level of trustworthy we hold in those systems. Cybersecurity Taxonomy Framework (CTF) is such a taxonomy that supports the creation of adversarial cyber attack-defence models, risk mitigation, and resiliency plans. It was initially applied to the maritime industry [152]. There is evidence that this framework has been successfully transferred to aviation sector and in this subsection we are about to investigate its broad applicability to the general transportation field especially railway sector.

It is stated by Haass et al., ([153]) that most of the on-board communication systems that used for aerospace navigation, air-to-air and air-to-ground information exchange, flight control, etc., were created without cybersecurity considerations. Efforts have been made for defending critical systems against disruptive events and thus mitigate the financial costs of adversarial cyber attacks. Such as Aircraft Communications, Addressing and Reporting System (ACARS)[154], Automatic Dependent Surveillance-Broadcast (ADS-B)[155], and System Wide Information Management (SWIM)[156]. However, the previous work mainly address cybersecurity challenges in an isolated fashion (i.e. system-by-system, protocol-by-protocol basis), rather than provides a systematic framework.

There are many analogues between the maritime and railway transportation sectors; whereas maritime has port operations, vessel traffic services (VTS), shipping line operations, vessel operations, and unmanned maritime systems, railway has train station operations, railway traffic management, railway line operations, train vehicle operations, and unmanned railway systems, respectively. Both sectors have manufacturing, cargo and passenger transport, and handoffs of passengers and cargo to other modes of transportation.

TTable 6.8 investigated the inviting AI-based cybersecurity application for understanding the vulnerabilities in the components of critical on-board systems — Reducing malicious railway cyber attacks by using Cybersecurity Taxonomy Framework (CTF). Evaluation is conducted regarding to the aforementioned transferability criteria from the maritime sector to railway e-maintenance domain. (summarise the overall extent of transferability possiblities, check other subsections in 6.4)

Table 6.8: TTable: Reducing malicious cyber attacks by using Cybersecurity Taxonomy Framework (CTF)

		Evaluation				
Dimension	**Criterion**	*Very High*	*High*	*Medium*	*Low*	*Very Low*
Congruence	*mission/aim/scope*	✓				
	previous experience		✓			
	failure severity				✓	
Significance	*potential effectiveness*		✓			
	impact	✓				
Similarity	*goal*				✓	
	domain characteristics			✓		
Maturity	*AI application*				✓	
	automation		✓			
Implementability	*technology*				✓	
	sustainability (costs and effort)			✓		

Source Domains: Maritime - Cybersecurity Taxonomy Framework.

Congruence. *mission/aim/scope* As mentioned earlier in this subsection, there are lessons that the various transport sectors can learn from each other in terms of cybersecurity since the other transport domains have a homogeneous demand for avoiding attacks from a variety of cyber actors, ranging from criminals and hacktivists, to spies, terrorists, and information warriors. *previous experience* numerous maritime-specific communication systems that used in ship-to-ship and ship-to-shore information exchange were created with cybersecurity in mind. For example, Automatic Identification

System (AIS), Global Navigation Satellite Systems (GNSS), and the Long-Range Identification and Tracking network (LRITN). *failure severity* It is clear that it is important to design, deploy, and maintain critical railway digital assets with appropriate adversarial models, risk frameworks and resiliency plans.

Significance. In this framework, a system is being evaluated would be isolated and reflected in the decision tree taxonomy. Dependencies and shared assumptions can be expressed with a language useful for the many constituents within the railway environment. Through the application of this framework, many cybersecurity issues can be addressed, including communication challenges that will be particularly important as unmanned and autonomous systems are incorporated into the shared railway platforms. Hence we evaluate *potential effectiveness* and *impact* as ”high” and ”very high” respectively in this table.

Similarity. A primary *goal* of the model we described here is to identify vulnerabilities in our systems rather than identifying threat actors. From this perspective, the objective this framework wants to achieve in the target domain is quite different from that of in maritime. The object lessons is that if we concentrate on who is trying to perform attack, we are mostly likely get it wrong because it is hard to predict threats and, in any case, as suggested above, threats are beyond control events. Vulnerabilities degree, on the other hand, are easier to identify, particularly if we think like an attacker.

Maturity. Currently, applications similar with Systematic Wide Information Management (SWIM) have not been effectively introduced into the railway domain, but the successful implementation in other transport domain and its transferred case examples among non-transport sectors have been identified. There are still a lot work to do for applying *Cybersecurity Taxonomy Framework* to the critical system surveillance. In terms of *automation*, The framework has shown a good automation score on identifying adversarial cyber attacks.

Implementability. Identifying vulnerabilities is only the first step in building a cyber defence shell and understanding the true potential impact of these vulnerabilities. Therefore, a risk assessment must be conducted on each vulnerability such that railway operators can determine which policy to make for managing these potential risks.

To sum up, a more intelligent paradigm based on the Cybersecurity Taxonomy Framework (CTF) has been proposed in this part for investigating the possibility of transferability towards railways. This framework has been demonstrated that it is capable for the creation of adversarial cyber attack-defence models, risk mitigation, and resiliency plans in the general transport sectors. However, if we want to implement it successfully in railways, prerequisite applications like Systematic Wide Information Management (SWIM) and risk assessment towards each identified vulnerability should be introduced.

7. Case Studies

One of the main recommendations provided in D1.3, when closing the DISCOVER phase of the project, was to define pilot case studies/demonstrators to investigate the effects of AI solutions on safety-related applications.

In this Chapter, *several potential pilot case studies* are proposed. Remarkably, they are indicators for future research and are not intended to be all addressed within this project. We will select a few of them to lead to *proofs of concept and benchmarks* within the RAILS project. The selection will be made taking into account that a pilot case study has to meet at least two among the following requirements, in order to guarantee its adherence to the objectives of the project:

- it falls into one or more application areas identified in D1.3;
- it allows to perform a transferability study along with at least one of the directions identified in Chapter 6;
- it has been suggested and/or supported by the project Advisory Board.

In the following, some possible case studies are introduced; some of them can be already detailed, others need to be further discussed with the railway stakeholders and the Advisory Board. Therefore, the final choice will be made as part of Task T3.2.

7.1. Case Studies Identification

Given the above considerations, we selected two possible case studies that could be interesting to address in the future: Level Crossings (LC) and railway station Digital Twins. The Level Crossing case study has been suggested by the Advisory Board. Additionally, we also found promising AI applications (described in sections 6.4.4 and 6.4.4) that could be further investigated and perhaps transferred and exploited to cope with LC Remaining Useful Life estimation and health monitoring. Differently, in terms of the the digital twins, we aim to limit our scope in creating digital record for station assets by capturing the real-world state of a transit hub and mirror it in a virtual world.

7.1.1. Level Crossing (LC)

According to the European Railway Agency for Railways (ERA), within the EU-28 countries from 2015 up to 2019, fatalities from level crossing accidents have accounted for about 30% of all the fatalities registered in railways scenarios [143]. In the context of safety, in recent years, attempts have been made to replace level crossings with subways or bridges [157], nevertheless, this replacement process is too expensive given the huge number of LCs (about 105 thousand) within the EU-28 countries. Since that, other methodologies should be adopted to increase safety and reduce accidents such as those proposed within the SAFER-LC project [158] (concerning new warning signalling systems, speed bumps, but also detection and risk evaluation systems based on machine learning) or those reviewed in [159] (mostly based on IoT and train-to-wayside communication). Also, reference [160] gave a complete review of suitable obstacle detection technologies and their associated algorithms that can be exploited to support risk reduction at Level Crossings, and analysed the combination of obstacle detection sensors with intelligent decisions layers (such as Deep

Learning models) as an opportunity to provide robust interlocking decisions. These solutions aim at increasing the level of safety at LCs, however, in this and the future documents related to the WP3, we will mainly address maintenance aspects. The purpose will be to understand to what extent AI-based solutions (specifically DL ones) could help to move from a scheduled-based or corrective maintenance towards a real-time monitoring of the Level Crossing allowing for predictive maintenance activities (i.e. detect and correct the failure before it occurs).

Therefore, as suggested by the Advisory Board, Level Crossings are a suitable case study to propose benchmarks or proofs-of-concept even in the context of the maintenance as, in our view, guaranteeing the correct functioning of LCs should be the first step in order to ensure safety and traffic availability. We aim at proposing an AI-based system capable of assessing the functioning status of both oldest and newest level crossings by leveraging non-intrusive sensors for their monitoring and Remaining Useful Life (RUL) estimation. Many systems, especially those safety-critical such as Level Crossings, must undergo specific certification processes; the compliance to those certifications might be invalidated by an intrusive approach, resulting in a very time-consuming and expensive re-approval process. In this context, non-intrusive sensors such as cameras and microphones may be highly suitable for our purpose as they could be applied to all kinds of level crossings, installed externally, and are easy to maintain.

7.1.2. Railway stations using Digital Twins

Digital twins-based software representations of a physical asset, system or process, are being used across the rail industry to improve the design, functioning or planning of a vast array of operations. Digital twin is a kind of software uses "real-world" data to create simulation scenarios that predict how a product or process would perform in the physical realm. The digital twin techniques use various sensors such as cameras, GPS receiver, and advanced learning algorithms to create an interactive 3D replica of the essential rail system. Conventional multi-dimensional models help designers build and implement more complicated system, while digital twins incorporate advanced data tools into the procedure of back-and-front feedback between the twin and its real-world counterpart. Digital twins capabilities can enable organisations to visually immerse their teams in the decision-making process, run various analytics to predict and produce different outcomes, and to track/manage the constant change that happens not just on the projects, but through the life cycle of rail assets. The convergence of digital twins and its deliverables identify asset types and location maintenance history, it's the connectivity that allows users to connect physical assets in the real world with their digital counterparts.It is promising to use digital twin technology to develop and devise 3D models of the stations through the existing information available (e.g. light detection/ranging, and point-cloud data), such that technical and visual accurate models of the stations can be conceived—which provides a valuable digital record of assets that can be utilised for many other scenarios, for example, reducing the need for further site visits, inevitable delays caused by the limited capacity of a station, and unnecessary maintenance costs for the station facilities.

7.2. Case Studies Description

7.2.1. Level Crossings

Generally, Level Crossings can be subdivided into two macro-categories: Passive and Active. *Passive LC* involves neither signals to notice incoming trains to the road users nor barriers; while, *Active LC* can involve warning signals, i.e. acoustic alarms and flashing lights, and also user-side protections, i.e. gate arms, bars, which can be automatically triggered by the approaching train or manually activated by human workers. Also, active LC can be manual or automatic. Focusing on Automatic Active LC, they work correctly if, once triggered by the train, the warning signals are activated and, after some seconds, the bars begin to close. Therefore, the level crossings are made up of several subsystems that must work properly together to ensure safe operability.

Beyond the particular implementation of these subsystems, which could also vary from model to model, we are interested in evaluating the health status and estimating the Remaining Useful Life of both the newest (which may be equipped with the latest technologies and sensors) and the oldest (which may not) Automatic Active LCs by leveraging non-intrusive sensors, particularly cameras and microphones. Therefore, the purpose is to build an AI-based system capable of assessing the functioning of Automatic Active LCs by exploiting video and audio data only. This approach would also have the great advantage of allowing us to consider the whole Level Crossing System as a black-box, focusing only on its behaviour, i.e. just evaluating its visible and audible output and estimating its deviations from the expected/nominal functioning. Worth mentioning, as discussed in Section 6.4.4, we could also build and exploit Digital Twins to estimate the RUL of Level Crossings, with particular emphasis on the gate arm, in case they are already equipped with proper sensors.

7.2.2. Railway stations using Digital Twins

From the perspective of Predictive maintenance scheduling and planning (Mentioned in section 6.1), machine learning algorithms in the digital twin help managers optimise and update their operations. Sensors throughout the entire system, in the places like switches, signals and stations, create massive data feeds these learning algorithms for analysing, such that they becoming more accurate over time. Many rail operators use digital twins to manage their timetables effectively and keep delays to a minimum level. Inspired by their use of this technology, we developed some interests in identifying any potential conflicts with timings or platforms (station infrastructures), so that the operating team could plan the timetable in a more efficient manner to prevent or reduce potential delays. After collecting necessary data (e.g. train acceleration/deceleration and braking performance), the digital twin-based simulation model is able to alter train timings and platform allocations, and it's performance would be evaluated in this model before inputted into the real-world timetable. Which would potentially make the station system more efficient and robust when abnormal event/unexpected congestion occurs, compared to the conventional or manual approaches.

8. Conclusions

The overall objective of this document, which represents the results of Task T3.1 in WP3, to investigate which AI methods already used in other transport and non-transport sectors could be exploited and translated into the rail sector in order to enhance maintenance and inspection operations. The analysis has been carried out starting from the findings and application areas identified in WP1.

First, an overview of the main current and emerging AI-based technologies in other transport (Avionics, Automotive, and Maritime) and non-transport (Manufacturing, Machinery, and Critical Infrastructure) sectors has been addressed. Second, based on the work performed in D2.1, a transferability framework has been defined through the identification of some transferability criteria, useful to make a qualitative evaluation of the AI-based applications' degree of transferability to railway.

Particular emphasis has been put on technologies including Digital Twins, IoT, Cloud Computing, and Drones to understand to what extent these can improve railway maintenance and inspection. Indeed, in chapter 6, we identified among the most premising transferable applications those oriented to **AI-aided fault diagnosis and prognosis through Digital Twins and IoT**, **AI-aided asset and bridge health monitoring based on autonomous UAV**, and **Vehicle Health Evaluation based on Big data management (IoT-based) and Cloud Computing**. Notably, to address **AI-aided asset and bridge health monitoring based on autonomous UAV** it is also possible to exploit, in future analyses, the advancements in AI-aided autonomous UAVs (as reviewed in D2.1 [126]) and the AI-based defect detection solutions that have already been proposed within the rail sector, some of which already leverage UAV images (e.g. [128, 129]). Sightly differently, applications aiming at **Motion-based RUL estimation through non-intrusive sensors** have yet to be fully developed and understood, based on our findings; however, in our view, this may be a game-chaining technology and deserves to be further investigated. Lastly, **Reducing malicious cyber attacks by using Cybersecurity Taxonomy Framework (CTF)** is also a promising and significant aspect we need to consider when implementing AI-based applications into critical systems or automated procedures. Due to the high-automation of the entire system, vulnerabilities are more likely to be penetrated by the cyber attackers.

It is worth mentioning that the smart-maintenance applications discussed in this deliverable can be used to guide the execution of maintenance tasks. In fact, AI techniques can support fully or semi automated inspection activities and also build decision support systems aiming at indicating the most suitable maintenance activity that should be performed based on appropriate fault detection and prediction. For instance, by predicting the Remaining Useful Life of a Level Crossing barrier, it would be possible to advise the replacement or specific maintenance actions aiming at increasing the RUL and system safety. Furthermore, a step-by-step decision support based on portable devices and augmented reality (such as the one enabled by smart-glasses) can be envisioned as a future development enabled by AI technologies.

However, concerns have been raised regarding the actual transferability of some of the identified AI applications given the differences in regulations and safety concerns that exist between the non-transport sectors and railways. Therefore, further detailed analyses will be needed to understand the practical risks of transferring a specific application by learning, for examples, from similar analyses already performed in other sectors (e.g. [20]).

By leveraging the results reported in D1.1, D1.2, and D1.3, and through a synthesis of the transferability analysis performed in this report, possible research directions have been identified. In particular, a set of pilot case studies have been selected, such as Level Crossings Remaining Useful Life estimation and health monitoring, and railway station digital twins-supported scheduling and planning, with the aim of identifying some roadmaps which will be further investigated within the RAILS project. The proposed transferability analysis represents a first evaluation of the possible AI techniques that could be transferred to the railway sector, while specific proofs-of-concept will be developed to identify the advantages and benefits that AI could provide to railway maintenance and inspection.

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