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Identifying the most suitable machine learning approach for a road digital twin

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Abstract

Road infrastructure systems have been suffering from ineffective maintenance strategies, exaggerated by budget restrictions. A more holistic road asset management approach enhanced by data-informed decision making through effective condition assessment, distress detection, future condition predictions can significantly enhance maintenance planning, prolonging asset life. Recent technology innovations such as Digital Twins have great potentials to enable the needed approach for road condition predictions and a proactive asset management. To this end, machine learning techniques have also demonstrated convincing capabilities in solving engineering problems. However, none of them has been considered specifically within digital twins context. There is therefore a need to review and identify appropriate approaches for the usage of machine learning techniques within road digital twins. This paper provides a systematic literature review of machine learning algorithms used for road condition predictions and discusses findings within the road digital twin framework. The results show that existing machine learning approaches are to some extent, suitable and mature to stipulate successful road digital twin development. Moreover, the review whilst identifying gaps in the literature, indicates several considerations and recommendations required on the journey to road digital twins, and suggests multiple future research directions based on the review summaries of machine learning capabilities.

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1. Background

The maintenance and management of road infrastructure is of great significance in any country for achieving a sustainable social and economic development. Therefore, there is an ongoing research question on how to achieve high quality for the operation and maintenance of roads within an optimised asset management strategy when facing insufficient funding (Burningham & Stankevich, 2005). In the UK, the cost of road maintenance activities for local roads, managed by local authorities, was up to £3.3 billion in the years 2016 to 2017 (Haylen, 2019). The maintenance activities are mostly carried out based on a reactive approach which involves heavy manual labour, enough to maintain the serviceability of roads. However, the reactive approach is not as cost-effective as the proactive approaches (UK House of Commons, 2019). One of the reasons that proactive maintenance strategies are not well adopted is a lack of a holistic management approach based on the reliable and accurate deterioration modelling and asset whole lifecycle data management (Bowden et al., 2006). The most recent trend in the field of infrastructure maintenance is leaning towards intelligent models informed by monitoring data for proactively optimised maintenance strategies (MJ DeJong et al., 2019). This requires consideration of (i) maintenance activities covering the whole lifecycle of the asset, (ii) relevant data that can be influential factors of asset performance, (iii) the quantified optimum balance of costs across different stakeholders including infrastructure owner, manager, and user. Due to the complexity of road types, materials, structures, and their degradation mechanisms shaped by large number of factors during their service life, it is extremely challenging to create precise maintenance strategies with a high level of granularity.

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On the other hand, recent developments in digital technologies such as Internet of Things (IoT), Big Data, Sensorisation, Machine Learning (ML) or Deep Learning (DL), and Artificial Intelligence (AI) have received increasing attention in resolving civil engineering problems (Karimzadeh, 2020). Among both academics and practitioners, road engineers have recognised that a large amount of data from a network of sensors can provide continuous and useful information on road behaviour and performance and is able to provide a more comprehensive understanding of the road status if combined well with visualisation (D Trousdale, 2019; Steyn, 2020). Specifically, with the growing number of real-time data from various sources, data analytics approaches have been leveraged to perform improved road deterioration modelling and to enable prediction with high accuracy for road performance (Piryonesi, 2019). With regards to road performance prediction, various ML neural networks and different DL algorithms have been explored to predict the road performance based on a data-driven method (Amirhossein Hosseini, 2020; Choi & Do, 2020). As a result of the evolvement of these technologies, a novel concept of digital twin has recently become a popular research area for architecture, engineering and construction management and has shown a great potential to support thorough intelligent automated decision-making as a visual-aided tool for the asset whole lifecycle management and therefore to optimise operation and maintenance strategies (Macchi et al., 2018). The report from National Infrastructure Commission - Data for the Public Good provided suggestions for the UK government toward a digital infrastructure and development of a national digital twin was the key element (NIC, 2017). The Gemini principles published by the UK Digital Framework Task Group and the Centre for Digital Built Britain

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also addressed the need of digital twins (Bolton, 2018). Various applications of digital twin

concept have been investigated for different assets at different levels. For example, at a city

level for buildings, Lu et al (2020) demonstrated successful implementation of a building

digital twin which integrates heterogeneous data sources and supports decision-making

processes in operational and maintenance management. As for the bridges, and at an asset level

Ye et al (2019) created a digital twin for structural health monitoring of bridges which provided

several benefits including efficient query of relevant data, integrated capabilities of data

processing and interpretation as well as a collaborative environment for various stages of a

bridge project. Yu et al (2020) presented a highway tunnel performance prediction model based

on digital twin concept and ML technique, which illustrated a reliable data-driven management

method for preventive maintenance. Comprehensibly, road being one of the fundamental assets

of any national infrastructure system, digital twins for roads would improve the accuracy of

prediction and through that the effectiveness of any associated decision-making. However, no

previous research has thoroughly investigated the potential applications of digital twin and its

involved capabilities for roads, especially with a focus on road condition prediction.

One key enabling element of digital twin is the ML or DL capability for classifications

and prediction of deterioration trends by taking advantage of the large volume of data available

in the industry 4.0 age (Fuller et al., 2020). For instance, ML algorithms have been used to

efficiently and effectively perform classification tasks on remotely sensed images (Maxwell et

al., 2018). With regards to road management, they have been utilised in classifying the types of

roads (Saleh & Otoum, 2020), and different road surfaces (Bibi et al., 2021; Menegazzo & von

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Wangenheim, 2021a) as well as forecasting future performance of roads (Marcelino et al., 2021).

Currently, digital twin has various definitions provided by different organisations and sectors. VanDerHorn & Mahadevan (2021) summarised more than 46 literatures related to digital twin concept and provided a relatively generalised and consolidated definition as follows, "a virtual representation of a physical system (and its associated environment and processes) that is updated through the exchange of information between the physical and virtual systems". Based on these definitions, there are multiple requirements for a digital twin which are summarised in Table 1. Considering current practices for road maintenance and the core functionalities and elements of an ideal pavement management system (PMS), a more specific list of requirements for road digital twin together with a detailed mapping with ML algorithms are presented in Table 1.

While various ML algorithms have been developed for modelling road deteriorations and to predict its conditions, none of these has been developed, tailored nor applied for a digital twin and its needs. Therefore, this research first takes a detailed look at the literature related to ML algorithms as a foundational basis for the road digital twin, in order to map the requirement of the digital twins against the ML capacities and applications. ML algorithms could have potential to assist and cover a broad range of road digital twin functionalities depending on the user requirements, such as traffic management and safety assurance. However, this paper then narrows down to describe and discuss the ML approaches and algorithms, identified through a systematic literature review, that could fit into a road digital

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twin to satisfy the requirements of road condition prediction applications.

2. Systematic review

A systematic literature review has been carried out to critically appraise and syntheses research findings on ML models for road conditions prediction. The systematic review described in this paper addressed the follow question:

- What are the most suitable ML algorithms or approaches to address the requirements of a road digital twin for the application of road condition prediction?

2.1 Definitions

The systematic literature review followed a search protocol which is based on the definitions provided in Table 2.

2.2 The adopted search approach

The first step was to define the search keywords to identify relevant articles according to three categories (Subject, Technology and Functionality), as described in Table 3, to identify the potentially relevant articles in different databases. The sources used in this systematic literature review were Google Scholar, ResearchGate, SAGE Journal, ScienceDirect (Elsevier), Scopus, Taylor and Francis, Transport Research International Documentation (TRID), Web of Science, and library database at the Universities of Birmingham, Nottingham, and Manchester.

A systematic literature review software (EPPI-Reviewer^{TM} Web version) (UCL, 2019) facilitated the review and was used for screening, coding, analysing, and storing retrieved articles (Thomas and Brunton, 2010). In particular, ML based priority screening function within

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the EPPI-Reviewer[TM] was utilised to help screening the large volume of articles as part of the review process (Tsou et al., 2020). The adopted systematic literature review process is summarised in Figure 1.

2.3 Weight of evidence: assessing the quality of studies

A weight of evidence (WoE) framework has been developed and used to assess the quality and suitability of the included studies in three categories - research soundness, appropriateness of study design to review question, and relevance of evidence focus to review question (see Table 4). The studies finally included and considered were required to score high rating in at least two categories and one medium rating on the third. If the study satisfies at least one of the points of the description ratings, the corresponding ratings are applied.

2.4 Synthesis of evidence

The data were synthesised to indicate the most suitable ML algorithms to best predict road condition considering within a road digital twin environment. More specifically, section 3 summaries different ML models, their inputs, output, data being used that would potentially have an impact on the model performance; and section 4 provides a further discussion on how these findings and insights could be contributed to the development of a road digital twin.

3. Summary of main findings

This section reports detailed findings on the selected studies after the Weight of Evidence stage. Although it is not within the scope of this review, to facilitate review findings summary, a potential road digital twin framework has been suggested (Figure 2) based on the large amount

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of literature reviewed, with a focus on road condition prediction within a road digital twin application.

Nine high quality studies based on the WoE analysis were identified to answer the primary review question. The given ranking for the nine selected studies during the WoE stage are presented in Table 5.

All the nine studies contribute to the understanding and definition of the requirements of a road DT as well as the suitability of up-to-date ML techniques. DT is a digital replica of the physical entity across its lifecycle, and therefore its prediction capacity for the road condition is vital, which could be achieved through a ML based approach. Various findings of the identified studies are synthesised and described in the following subsections. The following sub-sections describe findings in further details on the key elements shown in Figure 2.

3.1 Model input parameters

The systematic literature review indicates that researchers have considered a broad spectrum of different types of categories of parameters that could have an impact on the pavement performance and have used them as ML prediction model inputs. To summarise, the considered input parameters fall under below categories: Pavement structure, material, historical performance, traffic, environment, as well as maintenance treatment records.

Six studies (Alharbi, 2018; Fathi et al., 2019; Gong et al., 2018; Marcelino et al., 2019; Ziari et al., 2015, 2016) have considered the total thickness of the pavement structure as one of the model inputs, the results of the studies suggest that the range of pavement thickness have an impact on pavement performances, with a particular emphasis on cracking. As for the

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material, asphalt mixture air voids and the measured asphalt content have been utilised by three

studies to build prediction models (Fathi et al., 2019; Gong et al., 2018; Tabatabaee et al.,

2013). Fathi et al (2019) reported that air voids are one of the important attributes that

significantly affect fatigue cracking along with pavement age and thickness. Annual average

precipitation has been mostly considered to account for climate impacts on pavement

performance (Alharbi, 2018; Gong et al., 2018; Marcelino et al., 2019; Ziari et al., 2015, 2016).

This is an important factor for pavement condition forecasting to include the impact of

changing climate and on road deterioration. The reviewed ML models have proved its

capacities to quantify the impact of climate factors. For traffic loadings, equivalent single axis

load (ESALs) has been used as input for four studies (Bukharin et al., 2021; Tabatabaee et al.,

2013; Ziari et al., 2015, 2016) whereas annual average daily traffic (AADT) also has been

utilised in four studies (Gong et al., 2018; Marcelino et al., 2019; Ziari et al., 2015, 2016). It

appears that most studies either considered ESALs or AADT and not both at the same time.

However, Ziari et al (2015) considered both and presented that AADT has slightly more

importance on pavement performance prediction than ESAL by 10%. In addition, some studies

chose not to consider ESAL as it can be assumed to be equivalent to age (Abdelaziz et al.,

2018). Historical pavement performance metrics have also been identified as useful model

inputs by various studies. For instance, three studies used previous rutting values to predict

future road condition (Abdelaziz et al., 2018; Alharbi, 2018; Gong et al., 2018). Furthermore,

Abdelaziz et al. (2018) and Alharbi (2018) have investigated other road defects as road

condition indicators such as international roughness index (IRI) and crack rating for model

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development. Most studies have concluded that initial condition data is the most significant factor that determines the model performance (Alharbi, 2018; Fathi et al., 2019; Gong et al., 2018; Tabatabaee et al., 2013; Ziari et al., 2015). Last but not least, although maintenance data is an equally important information and a useful additional data source, few studies have utilised the data due to the potential difficulty to access them. Among the chosen studies, only one study has considered maintenance treatments as an input for the prediction model and have produced satisfying results ($R^2 = 98\%$) (Tabatabaee et al., 2013). Abdelaziz et al. (2018) also analysed maintenance impacts on the IRI values before and after the treatment, but it has only been used to identify and evaluate the corrected IRI values instead of maintenance type itself being prepared as an input to the model. It would be useful to understand ML's capacity in handing maintenance effects when making road condition predictions.

3.2 Model output parameters

Four studies (Abdelaziz et al., 2018; Marcelino et al., 2019; Ziari et al., 2015, 2016) have analysed IRI as the prediction model target output, noting that it has been used by many world transportation agencies as an indicator for pavement performance as well as maintenance and rehabilitation initiation factor (Abdelaziz et al., 2018). Moreover, Tabatabaee et al. (2013) have predicted present serviceability index (PSI) which is highly correlated with the IRI. The rest of the studies have focused on the forecasting of the future condition of the road with specific distresses, and in particular, cracking (Alharbi, 2018; Bukharin et al., 2021; Fathi et al., 2019) and rutting (Alharbi, 2018; Gong et al., 2018). In addition, this review also found that the output of ML model for different applications could potentially be expanded to detect and

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locate road defects (Ahmadi et al., 2021; Alzraiee et al., 2021; Arya, Maeda, Ghosh, Toshniwal, & Sekimoto, 2021), measure road temperature or wetness (Milad et al., 2021; Morris & Yang, 2021), classify roads based on intelligent inertial sensors (Lee et al., 2021; Menegazzo & von Wangenheim, 2021b), prioritise and plan maintenance (Gao et al., 2021; Han et al., 2020), as well as determine the remaining service life of pavements (Citir et al., 2021; Karballaeezadeh et al., 2019; Nabipour et al., 2019) depending on the requirements of the road DT.

3.3 Data used for research

Various data have been explored and used to develop prediction models using ML technique with unique data characteristics, pre-processing methods, and training and testing data split percentage, which are described in the following sub-sections.

3.3.1   Database

Six studies (Abdelaziz et al., 2018; Fathi et al., 2019; Gong et al., 2018; Marcelino et al., 2019; Ziari et al., 2015, 2016) have used US Long-Term Pavement Performance (LTPP) (Highway Administration and Pavement Performance program, 2017) which is a public database that provides state-of-the-art pavements information. The other three studies (Alharbi, 2018; Bukharin et al., 2021; Tabatabaee et al., 2013) used data sources from the pavement management systems (PMSs) owned by the US state transportation agencies. In addition, two studies (Gong et al., 2018; Marcelino et al., 2019) combined LTPP data with US National Cooperative Highway Research Program (NCHRP) permanent deformation model and reports and Portuguese national road administration database accordingly to increase the total amount

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of data. The reason behind the LTPP database being extensively researched by the pavement

scholars is because of its availability for public, and its comprehensive coverage of various

types and categories of data, such as structure and material, climate, traffic, and performance.

The number of considered road sections and data records also vary significantly for

different studies. Fathi et al. (2019), Gong et al. (2018), and Ziari et al. (2015, 2016) used data

from 26 to 88 road sections and obtained over 200 records for ML model development.

Meanwhile Abdelaziz et al. (2018), and Alharbi (2018) collected data from around 500 sections

resulting in average of 1,792 records to train and test the ML algorithms. However, other

researchers (Bukharin et al., 2021; Marcelino et al., 2019; Tabatabaee et al., 2013) utilised over

14,000 data entries for preparation of next stages such as data pre-processing, model

development and validation. The number of years covered in the utilised data ranged from five

to 31 years.

3.3.2 Data pre-processing

Road condition data often includes various measurement errors and missing values, and hence

it is essential to perform data pre-processing in order to achieve a relatively complete, clean,

and high-quality data set (Ziari et al., 2015). This would help ML algorithms to better identify

and understand the data and to eventually resolve the classification and regression problems for

future road condition predictions.

Four studies (Abdelaziz et al., 2018; Bukharin et al., 2021; Ziari et al., 2015, 2016) have

particularly addressed the issue of missing data. The methods used to fill missing values were 1)

linear interpolation, 2) removal 3) regression model. In addition, Bukharin et al. (2021)

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performed removal on irrational behaviours of the crack, ride, or rut ratings data. To increase the accuracy and the large variance in the collected data, Ziari *et al*. (2015) used data normalisation technique to prevent bias due to large differences between minimum and maximum values in datasets.

3.3.3 Split on training and testing data

Before developing any ML model, it is important to prepare specific data for training and testing purposes. The size of training data in the considered studies varies from 58% (Bukharin et al., 2021) to 90% (Ziari et al., 2016). However, it can be concluded that the most common practice has been using 80% of the data for training and 20% of the testing, which is the case for four studies (Fathi et al., 2019; Gong et al., 2018; Marcelino et al., 2019; Ziari et al., 2015).

3.4 ML algorithms and configurations

Among the nine chosen studies, two main approaches have been explored to achieve satisfactory prediction model results. One approach was to use single ML algorithm to train and learn from the data, while alternatively a combined ML algorithms method was used for model development. For the usage of single ML algorithm, neural networks with various neuron configurations in hidden layers have been adopted (Abdelaziz et al., 2018; Alharbi, 2018; Gong et al., 2018; Ziari et al., 2015). Among these studies, Ziari et al. (2015) with a three-layer neuron structure achieved the highest prediction accuracy (R^2 = 96.8% and Root Mean Squared Error (RMSE) = 0.14). In addition to neural networks, other algorithms such as support vector machines with Pearson VII Universal kernel (Ziari et al., 2016) and

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boosting-based learning algorithm - TrAdaBoost (Marcelino et al., 2019) have been utilised

and also produced a very high prediction accuracy (in average $R^2 > 85\%$). As for the combined

ML algorithms approach, it has resulted in a higher accuracy compared to the single ML

algorithms (in average $R^2 > 95\%$). As part of this combined ML approaches, the output of one

ML algorithm model was used as an inputs into another ML algorithm with the purpose of

improving the overall prediction accuracy. The explored algorithms are support vector machine

with recurrent neural network (RNN) (Tabatabaee et al., 2013); random forest with artificial

neural network (ANN) (Fathi et al., 2019); and long-term short memory neural network plus

ANN (Bukharin et al., 2021). Detailed ML algorithms and model accuracy for all nine studies

are presented in Table 6 below.

3.5 Types of prediction and accuracy

From the perspective of different prediction duration, most studies produced one year or one

step prediction, which is a basic capability of any ML models. But several studies have

developed the ML algorithm for the use of multi-year or multi-step predictions. For example,

Ziari et al. (2015) forecasted the IRI values for the next one year ($R^2 = 96.8\%$), two years ($R^2 =$

97.2%) and the whole lifecycle, i.e., three or over three years, ($R^2 = 97.9\%$). Moreover, the

study conducted by Bukharin et al. (2021) produced next $1 - 5$ years condition predictions on

crack ratings with a continuous high accuracy (in average $R^2 = 98.5\%$). Similarly, (Marcelino

et al., 2019) predicted the next one to four years with relatively little loss in performance (in

average $R^2 = 99.5\%$). One insight worth noting is the use of transfer learning which enables the

model to learn and extract the knowledge from multiple different databases and thereby

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increasing the overall prediction capacity.

3.6 Model Sensitivity analysis

Sensitivity analysis is another key component for any ML model development and analysis process. Five studies have provided a relatively in-depth analysis on the importance of each input parameter to the model output (Alharbi, 2018; Fathi et al., 2019; Gong et al., 2018; Tabatabaee et al., 2013; Ziari et al., 2015). Table 7 shows a summary of the most important input parameters ranking from #1 (most relevant) to #5 (least relevant) for different considered ML models.

4. Discussions

Based on the findings of systematic literature review, it can be understood that various databases, data analytics techniques and ML algorithms have been developed, trailed, and tested for modelling road deterioration and to predict the road condition. Having said that, none of the existing data analysis and ML algorithms has been developed, tailored nor applied for road DT context to accommodating its needs. Therefore, this section explores further on the review findings and discusses the potential applications of different types of ML algorithms, their configurations as well as the optimisations that could be applied within a DT framework especially formed on the basis of the high-level requirements defined by the Centre for Digital Built Britain (CDBB) (Bolton, 2018) as well as multiple definitions and requirements summarised by VanDerHorn and Mahadeva (2021).

4.1 Data collection and analysis

As described in Figure 2, data source module contains both historical and real-time data, using multiple sources and types of data are important requirements for a road DT to ensure high accuracy in showing the status of the asset and predicting its future condition. Possible data sources are historical road inspection surveys, existing public pavement performance database (e.g., LTPP (FHWA, 1995)), public image datasets for road damage analysis (Arya, Maeda, Ghosh, Toshniwal, Omata, et al., 2021; Atikur, 2020; Maciej Serda, 2013; Varma et al., 2018), ground penetrating radar (GPR) surveys, data from existing pavement management systems, IoT devices, smartphones, cameras, and intelligent sensors based on distributed acoustic sensing (DAS) which enable the collection of a broad range of types of data (Liehr et al., 2019). These various sources of data can then be fed into the road DT for further processing, analysing, and modelling for the specific applications of the DT.

It also can be inferred from this review that various types of ML algorithms are capable of being the enabler of a road DT regarding future condition predictions. However, all selected studies have focused on time static data which is collected at a fixed time or frequency. Large amount of data as well as a more frequent data (real-time or near real-time) is expected to be an essential part of a DT according to various definitions of the concept (Abramovici et al., 2017; Demkovich et al., 2018; Negri et al., 2017). The higher sampling frequency could potentially result in the improvement on the prediction accuracy of different ML methods and possibly help to identify pavement condition changes at an early stage although it may not be easy to determine a sampling ratio in practice due to variable factors influencing road performance

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(e.g., different ages of the roads and different road conditions). However, the higher sampling

could lead to big data, which further requires large storage and computations. Therefore, there

is a need for further research on ML pavement performance prediction model development

using big data concept and IoT platforms (Steyn, 2020) to understand the capabilities of

different ML algorithms to deal with higher frequency data collection mechanisms, especially

on the trade-off between the accuracy and sampling frequency (and intervals).

4.2 Data characteristics and ML algorithms choice

As it is mentioned in the definition and DT general requirements summarised in Table 1, DT is

built on data, while the data itself plays a decisive role in the development of a DT. Data

pre-processing and cleaning remain to be a fundamental factor in achieving high quality data

and subsequently reliable ML prediction modelling in a road DT scenario where data could

become larger in volume, variety, and velocity. Based on the review, an important finding is

that the performance of ML algorithm itself is largely dependent on the data in terms of its

structure, values, and patterns, where the same algorithm and configurations could result in

completely different prediction accuracy if applied on a different dataset. This might be another

potential research area where a road DT needs to have a process or algorithm in place to

intelligently identify the most suitable ML algorithm(s) for a given dataset. The selection also

depends on the needs of various users of the DT. The process or algorithm could provide a

platform, like a data lake (Redeker et al., 2021), where all potential types of ML algorithms can

be trialled to select the one with highest accuracy as the output. The findings from this review

suggest that ANN, RNN, Long-short-term memory (LSTM) and a boosting algorithm

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AdaBoost.RT would be helpful in a road DT environment as it gives high prediction accuracies for not only short-term prediction (e.g., 1 or 2 years) but also long-term multiple year predictions (e.g., 3, 5 or 10 years) (Bukharin et al., 2021; Marcelino et al., 2019; Ziari et al., 2015).

Another fundamental key requirement and characteristic of a DT from Table 1 is its dependency on quality and variety of data, as well the data science pipeline. Having said that, none of the studies has considered to perform feature selection first on the identified model input parameters, which is an important component as part of the standard process within ML prediction model development. This could be one of the future research areas to improve the accuracy and reliability of the developed ML models.

4.3 Road lifecycle analysis based on DT

According to the defined road DT requirements in Table 1, the ability to communicate and reflect the characteristics and functionalities across the entire lifecycle within different phases of the corresponding physical asset is a crucial factor for DTs. Although the review result only presents the use of ML algorithms for road condition predictions, various ML or DL algorithms have been applied and could be further improved on other aspects of road asset management lifecycle. These applications could also be considered in the road DT development. For instance, ML algorithms such as Conventional Neural Network (CNN) can be used on image data to perform on-going structural condition health monitoring or assessment (Azimi and Pekcan, 2020) and to automatically detect different types of pavement distresses using k-nearest neighbour (kNN) algorithm (Du et al., 2020). In addition, to the application of DT for

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health monitoring, distress identification, and performance prediction, it can also be used for

the maintenance treatments and rehabilitation strategy selections using DL or reinforcement

learning algorithms, which has been proven more effective in optimising maintenance planning

and budget allocations than traditional methods (Gao et al., 2021b; Yao et al., 2020).

While the management of the road during its operation phase is important, the benefit of

using ML capabilities within a DT environment for other phases of a road lifecycle cannot be

ignored. Therefore, future research directions could be on the development or improvement of

DTs for road design, construction, and demolition. Furthermore, as an ideal DT should be able

to reflect the whole lifecycle development of the physical asset, there is a great value in

understanding the framework and processes of integrating the usage of different ML, DL or

reinforcement learning algorithms at different stages of the lifecycle of the road DT that

altogether could enable its purpose, and fully realise the asset values that would result in

highest operation efficiency and the lowest cost for the asset owners and end-users.

4.4 Future pavement management system based on road DT

Furthering the discussion from Section 4.3, this paper identified a large number of articles on

the applications of ML algorithms for various road applications. Therefore, this section focuses

on discussing road DT applications in improving pavement management systems. As

mentioned by Kulkarni et al (2003), the existing key elements of pavement management

systems are 1) data collection and management; 2) pavement performance prediction; 3)

economic analysis 4) priority evaluation 5) optimisation and 6) institutional issues. For each

element, a specific road DT application can be developed, enabled by one or multiple ML

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algorithms. For example, a road DT for pavement health monitoring can be created using the

data from multiple sensors such as pressure cells, deflectometers, strain gauges, thermocouples,

moisture sensors, fibre-optic sensors, non-destructive testing surveys or other IoT devices, to

enable a constant monitoring of the pavement. This in turn enables to detect the formation of

road distresses such as internal cracks (di Graziano et al., 2020). ML or DL algorithms such as

genetic expression programming models (Majidifard et al., 2020) have been developed to

perform classification tasks to evaluate road surface conditions over time. With all the

available data fed into the road DT, additional applications can be created to use the data

leveraging that the identified ML or DL models in this paper can provide. The ML algorithms

can be used to firstly create more precise and dynamic prediction model which self-validates,

and updates based on constant data inputs. Secondly, with data from maintenance activities,

construction history and asset owner policy, finance, and user cost, road DT can then be used to

generate and analyse 'what-if' scenarios on maintenance planning. This will enhance asset

maintenance prioritisation at network or project level, by achieving maintenance optimisation

through taking into consideration the associated social and economic factors (Yao et al., 2020).

Maintenance optimisation could be achieved by understanding the right timing to perform the

most cost-effective maintenance treatment on the right location(s) of road network and sections

with the highest priorities. However, to enable the innovation of road DTs, the sharing of

various data across different departments and even organisations would be the number one

challenge due to data privacy and data security issues (Marai et al., 2020). Aforementioned

applications could be also presented in 3D pavement models via BIM-based PMS for improved

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visualisation compared to current 2D or GIS-based visualisation (D'amico et al., 2022).

4.5 Other factors

Road condition data often suffers poor quality regardless of its collection frequencies, while periodical inspection surveys often have missing values due to machine faults or human errors (Ziari et al., 2015). In addition, as sensor monitoring data also is subjected to some level of inaccuracies influenced by various factors and conditions (Oliveira et al., 2021), it would be necessary to take into consideration these uncertainties into the road DT framework. This can be done, considering a probabilistic approach for the DT environment, thereby achieving a more realistic and accurate model output. For instance, Yao et al. (2021) proposed a probabilistic ML model – Bayesian neural network to address the issue of uncertainty, which could be adopted within a DT context. Another possibility to address poor quality data could be combining physics-based modelling with ML algorithms to generate extra data from physics-based model to compliment the data quality issues faced normally by ML applications (Arias Chao et al., 2020; Willard et al., 2020).

It is worth mentioning that although the purpose of this systematic literature review was to be inclusive and avoid missing valuable relevant articles, given the fact that DT and ML are recent technological advancements, the articles before and including the year 2011 have not been considered in this review.

There are various functionalities for a road DT, depending on the user requirements, which might or might not be addressed by ML algorithms. For instance, a road DT could consider traffic and its management, and/or enhancing safety by minimising car accidents

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(variable speed limits) while ML has the potential to assist achieving these. However, this paper only focused on ML capacity for predicting road condition.

5. Conclusion

This study is the first systematic literature review summarising the ML algorithms used in road condition predictions, and specifically, attempting to identify the most suitable ML approach within a road DT framework considering the attributes and characteristics of DTs. From the review's results, it can be concluded that in order to fulfil the purpose of future performance prediction of a road, the corresponding DT should include at least the following categories of data inputs:

    1) Existing performance index;

    2) Existing distress condition;

    3) Materials;

    4) Structure;

    5) Climate;

    6) Traffic

    The main data outputs of the ML models could be 1) Future performance index and 2) Future distress condition. In addition, this study comprehensively reviewed different types of ML algorithms and approaches applied for multiple functionalities that a road DT should include from the perspectives of road condition assessment, road defect detection, future performance prediction as well as maintenance planning and optimisations. This review has provided a thorough synthesis of findings on ML techniques used for pavement performance

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prediction. Several articles have been identified to show promising adaptability with high ML prediction capability that could fulfil the road DT requirements.

From this systematic review, it can be concluded that the ML algorithms which have recently been applied in resolving various aspects of pavement management problems are the foundational building blocks for a road DT and they do certainly demonstrate enough maturity within DTs' context. The insights obtained from this review indicate that there are multiple potential future research directions for a successful road DT development. For example, real-time data analytics capability, optimum choice of ML algorithms, integration of various ML algorithms for different DT capacities and the inclusion of probability ML considerations are some of the research areas. Further exploration and development in DTs for road would allow transportation agencies to more intelligently and efficiently, design, construct, operate and maintain their road infrastructure systems.

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Table 1. Requirements for a general digital twin, road digital twin mapped against ML capacities / applications

		Requirements											
		Synchronization between Physical & digital[1,8,9,11]	Data quality & granularity[1,2,17]	Covers the entire lifecycle[3,6,13,16]	Real-time data[1,9,14]	Virtual representation[2,4,9]	Performance prediction[5,9]	Informs decision-making[6,8,13,14]	Probabilistic prediction[1,3,13]	Common data storage[3,12]	Coping with big data[7,13,17]	Project prioritisation[3,15]	Maintenance planning[1,10]
General digital twin		■	■	■	■	■	■	■	■	■	■	■	■
Road digital twin			■	■		■	■	■		■		■	■
ML capacities / applications	Automated data analysis		■		■						■		
	Data cleaning & pre-processing		■								■		
	Efficient handing of multidimensional data		■		■						■		
	Data-driven condition assessment		■	■			■						
	Classification algorithms for road defect detection			■									
	Performance prediction			■			■					■	
	Reinforcement learning			■				■				■	■
	Probabilistic simulation								■				

[1]Barricelli et al (2019) [2]Lu et al (2019) [3]Ye et al (2019) [4]VanDerHorn & Mahadevan (2021) [5]Abbott Dean (2014) [6]Macchi et al (2018) [7]Gandomi & Haider (2015) [8]Kaur et al (2020) [9]Jones et al (2020) [10]Errandonea et al (2020) [11]Zhang (2019) [12]Fuller et al (2020) [13]Tao et al (2019) [14]Hofmann & Branding (2019) [15]Boje et al (2020) [16]He et al (2021) [17]Chen et al (2014)

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Table 2. Search protocol definitions

Term	Definition	Reference
Digital Twin	Digital Twin is a virtual representation of manufacturing elements such as personnel, products, assets and process definitions, a living model that continuously updates and changes as the physical counterpart changes to represent status, working conditions, product geometries and resource states in a synchronous manner.	(ISO/ISO-AWI 23247, 2019)
Machine Learning	Machine Learning is a broad term encompassing a number of methods that allow the investigator to learn from the data. These methods may permit large real-world databases to be more rapidly translated to inform decision making.	(Brnabic and Hess, 2021)
Road Prediction Model	Prediction Model predicts future road conditions or performances, and it's used for assessing and prioritising maintenance treatment type and timing, and estimating life-cycle costs	(Kargah-Ostadi et al., 2019)

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Table 3. Study Search Keywords

Subject	Technology	Functionality
"Road" OR "Roads" OR "Pavement" OR "Pavements" OR "Highway" OR "Highways"	"Machine Learning" OR "Deep Learning" OR "Digital Twin" OR "Digital Twins" OR "Artificial Intelligence"	"Performance" OR "Condition" OR "Prediction" OR "Forecast" OR "Forecasting"

Table 4. Weight of evidence (Gough et al., 2017)

Weight of Evidence	Ratings	Descriptions
Soundness	High	- Explicit and detailed methods and results on data collection, cleaning, and analysis - Comprehensive model development, optimisation and evaluation based on ML principles - Compelling ML algorithm prediction accuracy ($R2 > 90\%$) - Critical comparisons with other studies or models
	Medium	- Satisfactory methods and results on data collection, cleaning, and analysis - Detailed model development and evaluation based on ML principles with satisfactory optimisation - Satisfactory ML algorithm prediction accuracy ($80\% < R2 < 90\%$) - Limited comparisons with other studies or models
	Low	- Unsatisfactory methods and results on the data used - No optimisation on model development and evaluation - Unsatisfactory ML algorithm prediction accuracy ($R2 < 80\%$) - No critical comparisons with other works
Appropriateness of study design	High	- Data comes from real world with extensive coverage. Frequency of collected data is high (weekly or monthly) - The prediction model input parameters cover at least the following five categories: Traffic, Climate, Performance, Structure, Material, and makes performance prediction for one and more years - Model outputs include one or more of the following aspects: distress condition, maintenance planning, and road lifecycle
	Medium	- Data comes from real world with limited coverage. Frequency of data collected is medium (yearly) - The prediction model input parameters cover at least three of the below categories: Traffic, Climate, Performance, Structure, Material, and makes performance prediction for one and more years - Model outputs include at least one of the following aspects: distress condition, maintenance planning, and

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	Low	• road lifecycle
		• Data comes from laboratory or simulation. Frequency of data collected is low (by-yearly)
		• The prediction model input parameters cover one or two of the categories of Traffic, Climate, Performance, Structure, Material, and makes prediction for one year only
		• Model outputs include only one of the following aspects: distress condition, maintenance planning, and road lifecycle
Relevance of the study focus	High	• The length of road sections chosen is greater than 100 meters
		• The historical data covers more than 15 - 20 years
	Medium	• The length of road sections is less than 100 and greater than 50
		• The historical data covers more than 10 - 15 years
	Low	• The length of road sections is less than 50
		• The historical data coverage is less than 10 years

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Table 5 Details of WoE analysis on selected studies

Selected studies	Research soundness	Study design Appropriateness	Study focus relevance	Ranking Justification
(Tabatabaee et al., 2013)	High	High	High	• Clearly explained the utilised ML algorithm structure and the associated mathematical equations. • Collected large amount of data with over 10,000 records enabled by sensor data for over 15 years • Considered more than 5 categories of data sources including structure, performance, traffic, climate, material, and maintenance records and plans
(Ziari et al., 2015)	High	High	High	• Used advanced data processing method, i.e., group method of data handling (GMDH) and performed in-depth model optimisation with large scale. • Collected sources of data are broad, covering performance, structure, traffic, climate, and material • The collected data covers large spectrum of characteristics, for over 17 years
(Ziari et al., 2016)	High	High	High	• Used the same data as (Ziari et al., 2015), and provided clear explanation on the ML algorithm, including cross-validation method on the testing data
(Alharbi, 2018)	High	Medium	High	• Demonstrated clear ML algorithm training and testing process with loss functions • Collected annual data for over 17 years with over 1,000 records in total, aimed at multiple output predictions (roughness, cracking and rutting) • Rated Medium in the study design appropriateness criteria mainly due to the

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				limited considered number of data sources
				• Conducted model sensitivity analysis to understand the parameters affecting the performance
(Abdelaziz et al., 2018)	High	Medium	High	• Provided clear hidden layer structure for the ML algorithm for model optimisation
				• Emphasised much on data processing and cleaning, as well as maintenance impacts, ensuring high quality data
				• Regarding model inputs, it mainly considered previous condition index as the fundamental information
(Fathi et al., 2019)	High	Medium	High	• Combined two ML algorithms and showed significant improvement with R^2 from 64% to 92%.
				• Collected data over 20 years across four climate zone in the US
				• It used cross-validation techniques in the ML model training, testing process to avoid overfitting issues in ML
				• Put an emphasis on material properties as data sources for prediction
(Marcelino et al., 2019)	High	Medium	High	• Combined two databases using transferring learning algorithms to make predictions with 99.5% accuracy for multi-year prediction
				• The types of considered data are performance, traffic, climate, structure
(Bukharin et al., 2021)	High	Medium	High	• Showed detailed ML model structure and evaluated model performance with existing baseline models
				• Used around 15,000 data records for over 20 years, and made multiple year predictions (e.g., 2-5 years) with the minimum accuracy of 98%
				• Considered different types of data including geometry, performance, traffic

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(Gong et al., 2018)	Medium	High	High	• Combined data from LTPP data with the information from Mechanistic-Empirical Pavement Design Guide (MEPDG) to improve prediction • Provided clear illustration on deep neural network, optimised with adaptive moment estimation, and focused on regularisation of overfitting of the model. It was rated Medium in the research soundness mainly due to the relatively lower model performance (e.g., less than R2 = 90%)

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Table 6. Summary on ML algorithms and relevant accuracies

Author(s)	ML Technique(s)	Model Accuracy
Tabatabaee (2013)	Support Vector Classifier + Recurrent Neural Network	R^2 = 98% RMSE = 0.135
Ziari (2016)	Support Vector Regression	R^2 = 91.69% RMSE = 0.2259
Ziari (2015)	Artificial Neural Network + Group Method of Data Handling (GMDH)	**Short term (1 year):** R^2 = 96.8% RMSE = 0.14 **Short term (2 years):** R^2 = 97.2% RMSE = 0.167 **Long term (lifecycle):** R^2 = 97.9% RMSE = 0.377
Marcelino (2020)	Boosting - TrAdaBoost algorithm for regression	R^2 = 99.5%
Gong (2018)	Deep neural networks	R^2 = 86.7% RMSE = 1.403
Fathi (2019)	Random Forest + ANN	R^2 = 91% RMSE = 10.9
Bukharin (2021)	LSTM + ANN	Year 1: R^2 = 99% Year 2: R^2 = 98% Year 3: R^2 = 98% Year 4: R^2 = 99% Year 5: R^2 = 98%
Alharbi (2018)	ANN	R^2 = 92% RMSE = 8.42
Abdelaziz (2020)	ANN	R^2 = 75%*

*This article was selected despite a lower overall accuracy than the threshold defined in the weight of evidence stage because the author presented the model goodness-of-fit with 86% in the paper

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Table 7. Summary for the sensitivity analysis for the considered ML models

| No.	Study	ML Algorithm(s)	Model output	Input (importance)				
				#1	#2	#3	#4	#5
1	Tabatabaee et al. (2013)	Support Vector Classifier + RNN	Next year's PSI	PSI	Maintenance is required	Structure	Season	Age
2	Ziari et al. (2015)	ANN + Group Method of Data Handling (GMDH)	IRI	Annual Average Precipitation	AADT	Annual Average Daily Truck Traffic	Pavement thickness	ESAL
3	Gong et al. (2018)	Deep neural networks	Rutting	Predicted rutting in the asphalt concrete layer	Air voids in asphalt concrete	Predicted rutting in the granular base layer	AADT	Annual average precipitation
4	Fathi et al. (2019)	Random Forest + ANN	Alligator deterioration index (ADI)	Age	Asphalt content of the mix	Voids in mineral aggregate (VMA)	Pavement Thickness	Air Voids
5	Alharbi (2018)	ANN	Riding index	Age	Temperature	Previous IRI	Thickness	Precipitation
			Cracking index	Temperature	Previous cracking	Age	Structural number	N/A
			Rutting index	Temperature	Thickness	Age	Previous rutting	N/A

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Figure 1. The systematic literature review process
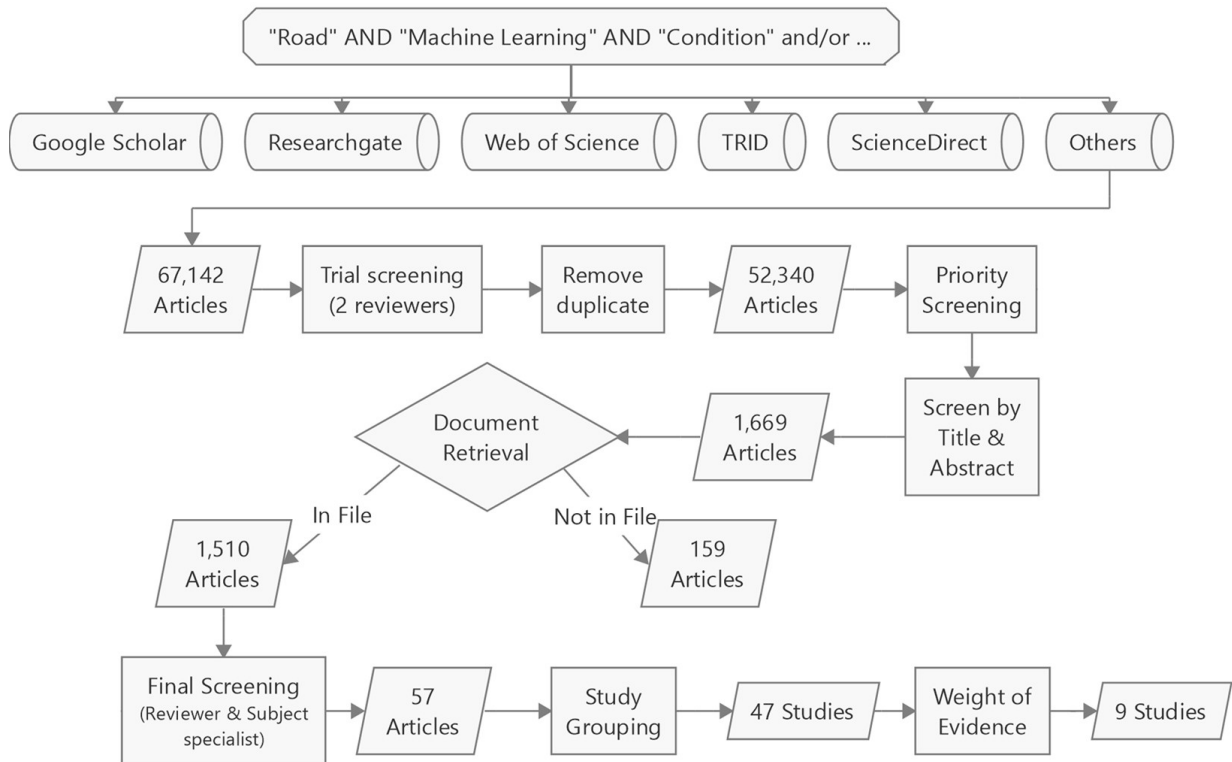
Figure 2. Digital Twin (DT) framework for road condition prediction