



# Digitizing and inventorying traffic control infrastructures: A review of practices

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## ABSTRACT

Transportation planning, management, and operation rely heavily on effective road asset management. As a crucial component of road assets, traffic control infrastructures (TCIs), such as traffic signs and traffic signals, play a pivotal role in managing traffic flows and enhancing road safety. However, in comparison to other road assets (e.g., pavements and bridges), the establishment and maintenance of TCI inventories remain relatively underexplored. This study presents an exhaustive review of current studies and practices concerning TCI digitization and inventorying by integrating a systematic literature review (SLR) with a narrative review (NR). The SLR synthesizes available data sources, models, and solutions for TCI detection and digitization, while the NR compiles essential modules and solutions for inventory establishment and maintenance. This study is among the first to approach TCI inventorying from an interdisciplinary perspective, providing a valuable reference for transportation researchers and practitioners engaged in road asset management.

## 1. Introduction

Transportation Asset Management (TAM) has been widely acknowledged as an essential component of transportation planning and management (Kumar, 2020, 2018; Miller et al., 2012). As a data-driven decision support solution, the TAM system enables transportation agencies to make decisions regarding investment, maintenance, and replacement of roadway assets, which has significant implications for providing safe and efficient transportation services to all road users (Kargah-ostadi et al., 2020; Kumar, 2019). In 2021, the Infrastructure Investment and Jobs Act (IIJA), with a historic \$1.2 trillion infrastructure bill, was signed into law in the United States. The IIJA aims to provide significant funding for building resilient, safe, sustainable, equitable transportation infrastructures with a clear need for road asset digitization and inventorying initiatives, especially through adopting innovative technology (such as remote sensing, the internet of things, and artificial intelligence) for asset management (The White House, 2021). Effectively establishing and managing an inventory database for roadway assets (such as asset types, locations, conditions, and dimensions) play an essential role in TAM (Transportation Officials, 2011).

Traditionally, road assets are manually digitized by conducting field studies, which is time-consuming and labor-intensive (Kargah-ostadi et al., 2020). With the advancement of data collection and processing techniques, road asset digitization and management have become a multidisciplinary process involving the integration of knowledge and skills from multiple fields, such as geospatial data science, computer vision, transportation management. For example, geospatial data science is of growing importance since numerous emerging data sources have become available, such as street view images, aerial terrestrial/airborne light detection and ranging (LiDAR), aerial/satellite imagery, and crowdsourced asset data. These data sources are offering new avenues and are increasingly implemented to capture and digitize road assets (Li et al., 2021; Sairam et al., 2016). More importantly, by combining these datasets with computational advances, such as computer vision techniques, a variety of road assets can be recognized from different imagery and non-imagery data sources. It is also worth noting that road asset digitization and management are often driven by transportation planning and maintenance objectives, such as improving road safety, reducing congestion, and enhancing transportation efficiency. This requires an understanding of transportation management principles in order to produce actionable regulatory frameworks for the road asset

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inventory build-up and upkeep. Therefore, conducting a comprehensive literature review from an interdisciplinary point of view is greatly needed to integrate solutions and advances from relevant fields to guide the establishment and maintenance of road asset inventory more efficiently.

As an important component of road assets, traffic control infrastructures (TCIs), such as traffic signs, traffic signals, and pavement markings, play a vital role in managing traffic flows and improving road safety. These TCIs provide information about the current state of the road, restrictions, prohibitions, warnings, and other helpful information for driving guidance (Wali et al., 2015a). Building and maintaining a TCI inventory not only can benefit transportation management, but more importantly, the digitized and timely updated TCI data could lay a solid foundation for promoting the deployment of connected and autonomous vehicles as well as the establishment of intelligent transportation systems (Kukreja and Mouftah, 2020; Yang et al., 2020a). However, compared to other road assets (e.g., pavement and bridges), the inventory establishment and maintenance for TCIs through mining emerging data are less explored. Therefore, there is a great need to review and summarize the current progress and challenges of using different geospatial data sources along with computer vision and data management techniques for TCI inventory buildup and upkeep.

To fill in this gap, this study used a mixed review approach by combining the systematic literature review (SLR) and narrative review (NA) methods to summarize the current state of practices, solutions, and challenges for TCI digitization and inventory development. We aim to provide a better understanding of how recent advances in spatial data science, computational science, and transportation management offer new opportunities for digitizing and inventorying TCIs and to help guide future research in this area. Please note that TCI includes a wide range of traffic assets, such as traffic signals/lights, traffic signs, pavement markings, lane markings, and intersections, among others. In light of the availability of existing studies, this paper primarily focuses on inventorying three main types of TCIs: traffic signals, traffic signs, and pavement markings.

The general workflow of TCI inventory establishment and management can be summarized into three modules: data acquisition, asset

extraction, and inventory establishment and management (Almutairy et al., 2021; Kargah-Ostadi et al., 2020), as illustrated in Fig. 1. Data acquisition aims to capture road assets using different data collection techniques. Asset extraction is the process of digitizing and localizing target objects from the collected imagery or non-imagery data. Inventory management is to establish and maintain a useful inventory tracking TCIs' information. Guided by this general workflow, this review aims to address three specific research questions regarding TCI digitization and inventory development, including: (1) Which data types have been utilized for TCI digitization? (2) What methodologies have been employed for TCI digitization? (3) What procedures have been implemented for the establishment, maintenance, and updating of TCI inventories?

This literature offers an interdisciplinary view of TCI inventory establishment by combining advances in multiple fields, such as data acquisition, computer vision, database management, and transportation management, among others. This study primarily contributes to transportation decision-makers and practitioners by providing a guideline on TCI inventory creation and maintenance. This study can also act as a valued reference helping data scientists to understand the landscape of available data sources and computer vision techniques (e.g., image classification, segmentation, object detection) and serves as a starting point to facilitate the digitization and inventorying of other road and urban assets.

The remainder of this paper is organized as follows: Section 2 introduces the review methodology. Section 3 shows the findings of data acquisition and processing methods in TCI digitization from the SLR and summarizes the modules and solutions for the inventory upkeep for inventory management identified through the NR. In Section 4, we summarize the key findings and further discuss the limitations and future research in TCI inventory management.

## 2. Method

### 2.1. Review method—a mixed review procedure

This study aims to achieve a comprehensive understanding of existing solutions supporting the TCI inventory build-up, summarized into three modules: data acquisition, asset extraction, and inventory establishment and management, as illustrated in Fig. 1. We first conducted an SLR because of its transparent and rigorous review procedure and its well-recognized capacity to generate a comprehensive understanding of a given topic. However, most identified literature through the systemic literature search is related to data acquisition and road asset extraction, while only a few are inventory relevant. We noticed that many inventory establishment and management works were published as grey literature, such as research reports, working papers, or technique manuals, which are generally not indexed by mainstream research article databases. To complete the understanding of the inventory build-up, we then contacted an NR to summarize the methods used in inventory establishment and management from supplementary literature. By combining an SLR with an NR, this mixed review procedure can result in a more complete and nuanced understanding of the complete workflow of TCI inventory establishment and upkeep so as to conclude a framework for TCI inventory management.

SLR has been widely applied to build new frameworks and perspectives on a topic based on comprehensive understanding by reviewing, critiquing, and synthesizing representative literature on that topic (Torraco, 2005). Note that the specific SLR procedures could vary depending on the type of literature review, but in general, the whole literature review process could be accomplished through the following eight steps: (1) formulating the research problem; (2) developing and validating the review protocol; (3) searching the literature; (4) screening for inclusion; (5) assessing quality; (6) extracting data; (7) analyzing and synthesizing data; (8) reporting the findings (Xiao and Watson, 2019). In this study, the SLR is primarily used to summarize the data sources,

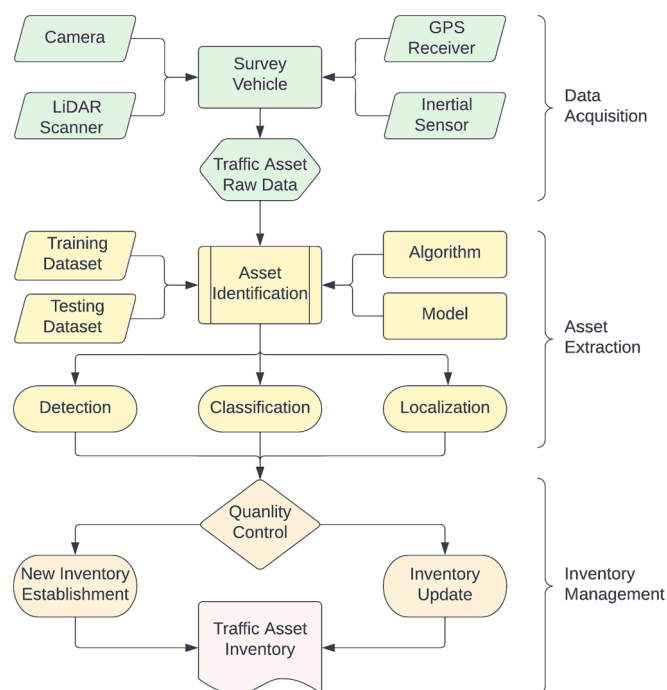


Fig. 1. Conceptual workflow for TCI inventory establishment and management.

methods, and models utilized to digitize TCIs.

Compared to SLR, NR was commonly used for obtaining the perspective on a topic of interest that usually does not involve a stated hypothesis. Unlike SLR which starts from a long list of all relevant articles, NR primarily search for pivotal papers known to the researcher (Li et al., 2022; The University of Alabama at Birmingham, 2022). In this research, we performed a narrative search to review the inventory-related articles and summarize a framework for inventory management based on the review result.

## 2.2. Literature search

### 2.2.1. Databases

This study performed a literature search on four research literature databases: IEEE Xplore (IEEE), Web of Science (WoS), Transport Research International Documentation (TRID), and Google Scholar. WoS and Google Scholar are among the most comprehensive academic literature databases (Martín-Martín et al., 2018). Google Scholar is a free search engine that indexes academic publications across a wide range of publishing formats and disciplines. WoS is a paid-access platform with articles manually checked based on their defined scholarly and quality criteria, which has higher academic reliability than Google Scholar. IEEE and TRID focus more on specific themes: IEEE is a research database majorly for journal articles, conference proceedings, and other scholarly materials about computer science, electrical engineering, and electronics; TRID is more expertized in the literature on transportation studies. Since our review scope covers multidisciplinary components from data science, computer science, and transportation, IEEE and TRID fit the review scope well, which can help build a comprehensive collection of relevant publications.

### 2.2.2. Screening and eligibility check

The SLR establishes a literature inventory through keyword searching, which inevitably includes irrelevant or redundant papers. Therefore, a screening and eligibility check is needed to manually select the relevant literature aligning with our research topic, questions, and objectives. In this study, the screening and eligibility check was completed by two independent reviewers through three steps: title screening, abstract screening, and full-text screening. Please note that some articles are accessible from multiple databases, resulting in duplications in the selected papers. The duplicated articles were manually removed through the title screening step.

To select the most relevant literature, we established two sets of selection criteria, as listed in Table 1. As defined in the inclusion criteria, the selected studies need to be either relevant to the digitization of TCIs or the establishment and management of road asset inventories. Meanwhile, we proposed four exclusion rules for filtering articles that focus on specific topics, such as TCI detection or recognition under extreme conditions or only talking about algorithms for image-based asset recognition. Meanwhile, this review also excluded articles published before 2002 or written in non-English languages.

**Table 1**  
Literature selection criteria.

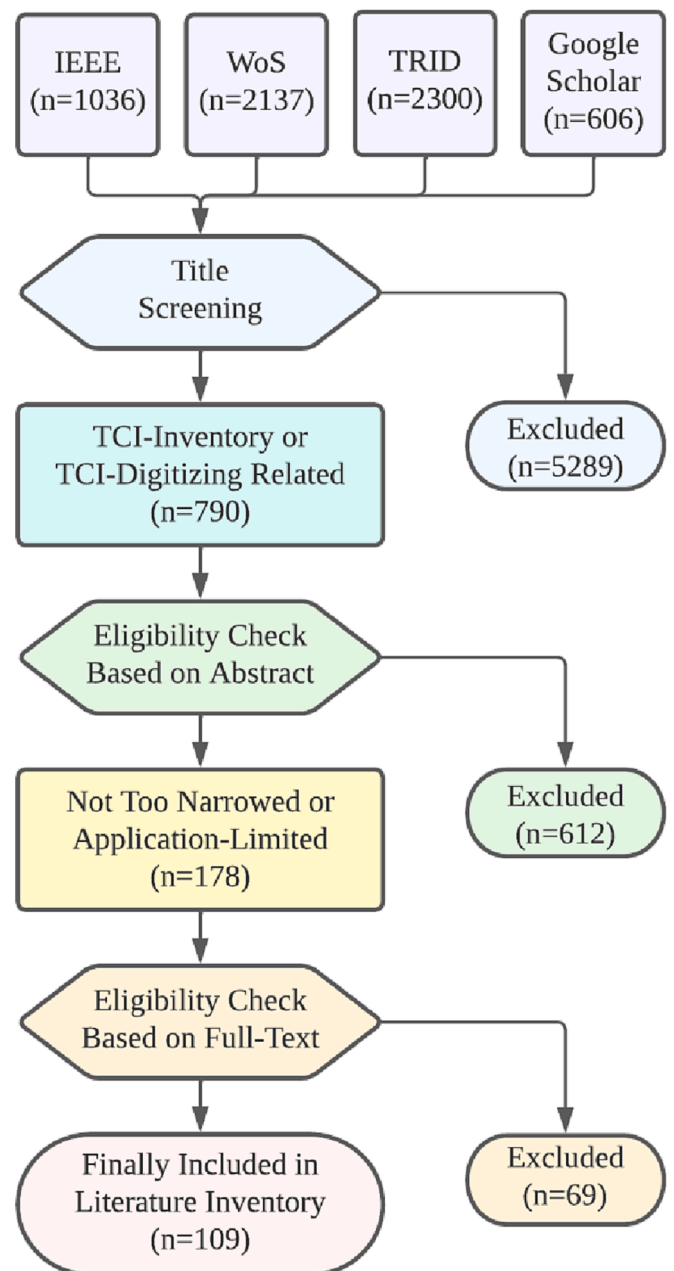
Type	Criteria
Inclusion 1	The article is relevant to the establishment, maintenance, or update of the inventory database of TCIs.
Inclusion 2	The article is relevant to the detection, recognition, or positioning of TCIs.
Exclusion 1	The article focuses on the methods only under extreme environmental conditions.
Exclusion 2	The article is specifically about the establishment of algorithms.
Exclusion 3	The article is dated (before 2002), or the methods discussed in the article are too outdated (hardly appear in other articles after 2002).
Exclusion 4	The article is not written in English.

## 3. Results

This section presents the review results for both SLR and NR. We first present the SLR result documenting the existing data sources, methods, and models utilized to digitize TCIs. Then, we summarize a framework for TCI inventory management based on the findings from the NR.

### 3.1. SLR literature search results on TCI digitization

Fig. 2 illustrates the whole process of searching, screening, and eligibility check performed in the SLR. The literature search was accomplished in Oct 2021. We started with 6,079 articles, including 1,036 from IEEE, 2,137 from WoS, 2,300 from TRID, and 606 from Google Scholar. Through title screening, 5,289 articles were identified as irrelevant or duplicated and were thereby excluded. For the remaining 790 articles being passed to the eligibility check, 612 were identified as over-specific or too narrowed and thus excluded as well.



**Fig. 2.** Workflow of literature screening and eligibility check.

Finally, through an eligibility check based on full-text reading, 109 articles were identified as topic-relevant, technique-applicable, and up-to-date to our research.

### 3.2. SLR result of data sources for TCI digitization

According to the review result, two types of data were majorly captured for inventorying TCIs, including TCI information and TCI location.

TCI information is majorly derived from two kinds of raw data: imagery (including street view images and videos) and LiDAR point cloud (Landa and Prochazka, 2014; Li et al., 2021; Nie et al., 2012). Street-scape images provide 2D visual information for the road assets, which can be processed through computer vision algorithms to recognize and extract TCIs. However, they provide limited information about the depth and can have occlusions and shadows (Siegmann, 2008; Tsai, 2012). LiDAR point clouds can provide detailed 3D information about a scene. Compared to streetscape images, LiDAR works better in night-time or low-light conditions for identifying TCIs with specific geometric shapes and characteristics. However, the data density depends on the sensor's resolution and can have missing or noisy data issues (Landa and Prochazka, 2014; Wang et al., 2017). Both types of data are usually captured using vehicle-based collectors (camera/LiDAR scanner). While vehicles run along the roads in the targeted area, the equipped camera captures images at a certain frequency or records videos or the LiDAR scanner scans points around the vehicles. Some researchers run the survey vehicles at different times of the day (e.g., morning, noon, dusk, and night) under various weather conditions (e.g., clear, rainy, foggy, etc.) to collect sufficient data that promote the performance of TCIs detection and classification (Feng et al., 2019). In addition, some survey vehicles are equipped with devices for in-vehicle data preprocessing, such as quality checks and data fusion, which can enhance the efficiency of developing TCI inventories (Almutairy et al., 2021; Kargah-Ostadi et al., 2020).

For the TCI location, GPS is the primary source for obtaining the location data. Some studies also implemented inertial measurement to enhance the location accuracy. The positioning equipment like GPS receivers and inertial measurement units (IMUs) are typically installed on survey vehicles (Almutairy et al., 2021). Please note that the collected location data refers to the location of the survey vehicle, not TCIs; thus, a series of post-process is necessary to calculate the physical location of the targeted TCI (Hazelhoff et al., 2014a, 2014b, 2012).

### 3.3. SLR result for TCI extraction methods

The general process for extracting TCIs from the collected data can be divided into three modules: detection, classification, and localization. TCI detection aims to identify the potential road sign regions from the images (a.k.a. Regions of Interests [ROIs]) and independently retrieve the pixel locations of all present road signs in each collected image. The classification module is performed to recognize the type of each detected TCI. The localization module retrieves/estimates the real-world positions of the detected signs. Note that some advanced methods that combine the detection and classification tasks can be implemented (see Section 3.3.3).

#### 3.3.1. Image-based methods for TCI detection

Imagery is the most used data source for TCI detection. Imagery-based TCI detection methods can be classified into two categories based on their principles: color-based and shape-based.

Color-based detection relies on the fact that TCIs, such as traffic signs, usually have distinctive colors, which can be used to differentiate them from the surrounding environment. Many color-based segregation methods have been implemented based on the different color spaces to identify the ROIs within the input image (Filatov et al., 2018; Wali et al., 2015a; Zhao et al., 2017). The most used color spaces include Red Green

Blue (RGB), Hue Saturation Value (HSV), Luma Chroma (YUV), among others. The commonly used color-based algorithms include color thresholding (Wali et al., 2015b; Wali et al., 2019), histogram-based thresholding (Daraghmi and Hasasneh, 2016), region growing (Chang and Li, 1994; Deshmukh et al., 2013), and machine learning algorithms using color features (Khalid et al., 2018; Wali et al., 2019), which are detailed in Table 2.

Shape-based methods rely on the distinctive geometric shape of TCIs (e.g., circle, triangle, rectangle, octagon) rather than their colors. Compared to color-based methods, shape-based methods are more advanced at tolerating environmental influence (e.g., weather

**Table 2**  
Image-based traffic sign detection methods.

Category	Typical algorithms or models	Reference
Color-based methods	Color thresholding: It is a common technique for segmenting an image based on its colors. It processes the image by setting a threshold for the colors and then segment the image based on the pixels that meet that threshold.	(Wali et al., 2019, 2015b)
	Histogram-based thresholding: It is a technique for segmenting an image into foreground and background regions based on pixel intensity values. It computes the image's color histogram and then sets a threshold based on the histogram.	(Daraghmi and Hasasneh, 2016)
	Region growing: Color-based region growing segments an image based on color similarity. This algorithm starts with a seed pixel or region and iteratively adds neighboring pixels with similar color characteristics until the desired ROI is obtained.	(Chang and Li, 1994; Deshmukh et al., 2013)
	Machining learning algorithms: Different supervised and unsupervised machining learning algorithms are also efficient for separating foreground and background pixels based on the color features. Commonly used methods include K-Means clustering, SVM, Random Forest, and CNN.	(Khalid et al., 2018; Wali et al., 2019)
Shape-based methods	Template matching: It uses a pre-defined template/shape of the traffic sign to match against the image pixels. If the shape of the traffic sign in the image matches with the template, it is identified as a traffic sign.	(Jia et al., 2020; Pandey and Kulkarni, 2018)
	Hough transform: It is a feature extraction algorithm. It converts the image space into a parameter space, where points that lie on the same line or curve in the image space are grouped together in the parameter space.	(Almutairy et al., 2021; Shekar and Harish, 2021)
	Contour detection: Contour detection algorithms can be used to distinguish the boundaries of traffic signs from images by implementing edge detection algorithms such as Canny edge detection or Sobel edge detection.	(Taki and Zemmouri, 2021; Yu et al., 2018)
	Distance transform matching: It first detects the object boundaries by performing edge detection algorithms. Then it assigns a distance value to each pixel based on its distance to the nearest object boundary.	(Gavrila, 1999; Khalid et al., 2018)
	Harr feature-based cascade classifier: It generates a set of simple rectangular features to represent an image region's texture and contrast information. These features are combined into a cascade of classifiers to determine whether a given image region contains the traffic signs.	(Pronchuk and Yakimov, 2018)



conditions and times of day). Table 2 lists commonly used algorithms, which include template matching (Jia et al., 2020; Pandey and Kulkarni, 2018), hough transform (Almutairy et al., 2021; Shekar and Harish, 2021), contour detection (Taki and Zemmouri, 2021; Yu et al., 2018), distance transform matching (Gavrila, 1999; Khalid et al., 2018), and Harr feature-based cascade classifier (Pronchuk and Yakimov, 2018). Note that the performances of the shape-based methods may not be satisfactory when the targeted objects are damaged or obscured.

To achieve a robust detection result, some studies combined color-based and shape-based methods where the candidate ROIs are extracted based on the color threshold and are filtered by shape template match (Ellahyani et al., 2017; Haar and Safran, 2012; Wali et al., 2015a). In recent years, some learning-based methods have been implemented to enhance ROI extraction (Almutairy et al., 2021; Feng et al., 2019).

### 3.3.2. LiDAR-based methods for TCI detection

LiDAR data is commonly used to detect road markings. Two features of road markings make them suitable to be detected through LiDAR data. First, most road markings are decorated on asphalt concrete pavements with highly light-reflective coatings such as yellow or white, leading to higher reflected intensity values that can be easily recognized when scanned by LiDAR scanners (Ma et al., 2021; Yang et al., 2020b). Second, similar to other traffic signs, road markings also show linear features with known width and length. The shapes and arrangement of road markings provide semantic information for target extraction and recognition (Yang et al., 2012).

Road marking detection using LiDAR data can be generally divided into two steps: road surface extraction and road marking extraction. The raw LiDAR data capture not only the road surface but also other objects like trees, cars, or buildings, and even some isolated LiDAR points in the air. Therefore, road surface extraction is needed to remove those non-ground points. There are different ways to accomplish this step, such as the elevation-based method and intensity-based method (Cheng et al., 2017; Yan et al., 2016). Usually, the filtered points are then converted into 2D geo-referenced images based on the reflection intensity for road marking extraction and classification (Yu et al., 2015). Once the 2D reflection intensity image generated, road markings can then be isolated from it based on their distinctively high values in terms of reflection intensity. In the resulted intensity images, the brightness indicates the reflection intensity and thereby, researchers could use various algorithms to identify the edges or shape boundaries of the road markings of interests (Ma et al., 2021; Yang et al., 2012). For example, Yang et al. (2012) implemented a Progressive probabilistic Hough Transformation (PPHT) method, which is a variation of the standard Hough transform to extract the linear features from the georeferenced reflectance intensity image. Yan et al. (2016) implemented an Edge Detection and Edge Constraint (EDEC) to detect road markings. They first organized the filtered LiDAR points clouds into scan lines. Then they extracted road marking points from road points by detecting the edges between road surface and road markings in scan lines. More commonly used algorithms for road surface detection and marking detection are listed in Table 3.

Although less common, some researchers have investigated the use of LiDAR-based methods for traffic sign detection. Similar to road marking detection, reflection intensity is the primary feature used to extract traffic signs. Due to the properties of LiDAR data, the detected traffic signs via LiDAR-based methods are always in three-dimensional space, which makes it possible to gain accurate information not only about the location and shape of the signs, but also the orientation and position of the sign bases or poles, which are much more complex to calculate via imagery-based methods (Javanmardi et al., 2019; Landa and Prochazka, 2014).

The most significant limitation of LiDAR-based methods is their inability to provide color information of traffic signs, making it necessary to pair LiDAR data with imagery data to obtain this information. It is worth noting that researchers could calculate the color deterioration

**Table 3**

LiDAR-based detection for road surface and markings.

Module	Typical algorithm or models	Reference
Road Surface Extraction	Positioning and orientation system (POS): record the height of LiDAR scanner to the scanned surface and thus identify if there are any off-ground points.	(Yang et al., 2020b)
	Voxel-Based Normalized Cut Segmentation: partitions point cloud data into an octree structure with a voxel size and expand the octree until it reaches the top boundary; the point clouds with top voxel higher than a certain threshold will be filtered out from the road surface.	(Cheng et al., 2017; Yu et al., 2015)
Road Marking Extraction	Progressive probabilistic Hough Transformation (PPHT): a variation of the standard Hough transform to extract the linear features from the georeferenced reflectance intensity image; in addition to the orientation, it also computes an extent for individual line-shaped road marks.	(Yang et al., 2012)
	U-Shaped Capsule Network: a capsule network that consists of traditional convolutional layers, primary capsule layers, convolutional capsule layers, and deconvolutional capsule layers; it can derive the shape and position information of the road markings.	(Ma et al., 2021)
	Hybrid Capsule Network: this network consists of a convolutional capsule network and an FC capsule network, and it can categorize these road markings by encoding high-level and low-level features from input images.	(Ma et al., 2021)
	Edge Detection and Edge Constraint (EDEC): this method detect the edges of road surface and use these edges to constrain the search space for road markings. It organizes preprocessed LiDAR points clouds into scan lines. It then extracts road marking points from road points by detecting the edges between road surface and road markings in scan lines.	(Yan et al., 2016)

in the imagery by examining the reflection intensity of the targeted traffic signs derived from LiDAR data (Landa and Prochazka, 2014). Therefore, the combination of LiDAR and imagery is expected to maximize the performance of traffic sign detection in this regard.

### 3.3.3. Methods for TCI classification

After the TCIs have been detected from the input data, we need to recognize the content of these TCIs and recognize their types. As shown in Table 4, TCI classification methods could be broadly classified into two categories: methods performed on created features and deep-learning-based methods.

The general classification methods are conducted based on a set of features to distinguish different objects. First, some methods can be applied to extract the targeted features, such as HOG, HOG variations (e.g., pyramid HOG [PHOG], HOGv) (Huang et al., 2017; Li et al., 2015), and Integral Channel Features (ICF) (Mogelmose et al., 2015). Based on these features, various models can be implemented to classify the traffic sign types, such as SVM (Wali et al., 2015b), AdaBoost (Balali and Golparvar-Fard, 2016), Tree-based models (Haar and Safran, 2012; Tsai et al., 2009), Template Matching (Peker et al., 2014), among others. These models use learning algorithms to classify each input traffic sign image. For example, Fig. 3 illustrates how a tree-based model distinguishes road sign types based on the generated shape and color features (Haar and Safran, 2012).

Deep learning methods also have been implemented for TCI classification, which has acquired a general interest in recent years because of its high performance in road asset classification and the power of

**Table 4**

TCI classification methods.

Category	Typical algorithms and models	Ref
Methods performed on created features	Support Vector Machine (SVM): a supervised learning method that constructs a hyperplane to separate data into classes. The “support vectors” are data points that define the maximum margin of the hyperplane. This lightweight classifier was intensively utilized by existing studies, which can potentially handle the classification in real-time.	(Wali et al., 2015b)
	Adaptive Boosting (AdaBoost): a combination of multiple learning algorithms that can be utilized for regression or classification. AdaBoost assigns weights to weak classifiers based on their quality. The resulting strong classifier is a linear combination of weak classifiers with the appropriate weights.	(Balali and Golparvar-Fard, 2016)
	Tree-based models: a series of “if-then” rules to generate predictions from one or more decision trees. All tree-based models can be used for either regression or classification, and sometimes certain decision rules form a set of criteria could judge the traffic sign candidates by their various properties.	(Haar and Safran, 2012; Tsai et al., 2009)
	Template matching: this kind of methods are used to search for existing similar training samples. The training samples were pre-characterized by a set of features. The input is compared with different pre-coded samples to examine their similarity. The input type will be assigned as the same as the most similar sample.	(Peker et al., 2014)
Deep-learning-based methods	Convolutional Neural Networks (CNN): a computational processing network system inspired by biological nervous system, which comprised of neurons that self-optimize through learning, loading input image vectors and making decisions as outputs after being processed by multiple hidden operation layers. (O’Shea and Nash, 2015)	(Smitha Shekar and Harish, 2021; Yang et al., 2020a; Yu et al., 2018)
	Extreme learning machine (ELM): a single-hidden-layer feedforward neural network (SFNN) that encapsulates all classes of traffic signs. It only estimates the weight vector between the hidden and output layers using a least-square strategy. Therefore, its computational cost drops very much and is easy for parameter tuning.	(Huang et al., 2015)

representational learning from raw data. Deep learning methods use a cascade of hidden layers in the neural network for extracting and transforming features. The output from the previous one is used as the input for the successive layer. Higher-level features are derived from lower-level features to form a hierarchical representation. Among the deep learning models, convolutional neural networks (CNN) are widely

used in image classification (Smitha Shekar and Harish, 2021; Yang et al., 2020a). CNN-based detectors prevail in object detection tasks. Unlike manually labeled features, CNN-based detectors use different convolutional layers to extract features directly from raw images (Yu et al., 2018). In addition to CNN, some other similar neural network models are also popular in deep-learning-based TCI classification methods, such as the Extreme learning machine (ELM) (Huang et al., 2015).

### 3.3.4. Detection and classification integrated deep learning methods

The advances in deep learning techniques offer plausible solutions to object detection and classification tasks. Some networks even could complete the detection and classification within the same model. Some state-of-the-art object-detection networks, such as Fast Region-Based CNN (Fast R-CNN) (Bengtson et al., 2018), Faster R-CNN (Almutairy et al., 2021; Deng, 2019; Pan et al., 2019) Mask R-CNN (Tabernik and Skocaj, 2020), Single Shot Detector (Ahsan et al., 2019; Lopez-Montiel et al., 2019), and You Only Look Once (YOLO) (Almutairy et al., 2021; Song et al., 2021), combined with various feature extractors (Resnet V1 50, Resnet V1 101, Inception V2, Inception Resnet V2, Mobilenet V1, and Darknet-19) are used for traffic sign recognition.

### 3.3.5. Methods for TCI positioning

The geolocation of the detected TCIs is critical for establishing TCI inventory. The positioning procedure of TCIs could be broadly divided into three modules: GPS-based vehicle positioning, inertial-based correction, and image-based asset localization.

**GPS-Based Vehicle Positioning:** GPS is the most direct and straightforward method and also the most basic step for collecting position data of the targeted TCIs. Usually, the positioning data using GPS are collected at the same time as the imagery data when running the survey vehicles where the GPS receivers are installed along with the camera or LiDAR scanners. For every point where the road data is captured, the corresponding coordinate data would be recorded as well (Almutairy et al., 2021; Hata and Wolf, 2014; Yang et al., 2018).

**Inertial-Based Supplement and Correction:** GPS receivers could sometime be blocked from the signals for some reasons (due to forests and high buildings). In this case, some inertial-based methods and instruments are utilized as supplements and corrections to GPS-based methods. When a GPS receiver loses the signals, the inertial instrument will record the movement of the vehicle, thus calculating the current position based on the last position data recorded by the GPS receiver. Thereby, the survey vehicles can keep collecting positioning data until GPS receivers regain the signals. Inertial-based methods include inertial measurement units (IMUs), distance measuring instruments, and an inertial reference system (Almutairy et al., 2021; Strain et al., 2020).

**Image-Based Asset Location Calculation:** For both GPS-based positioning methods and inertial-based correction methods, the collected position data generally represents the location of the vehicle, not the targeted TCIs. To solve this issue, image-based methods could be used to calculate the physical position of the targeted TCIs. This kind of method mainly obtains the position data by connecting the same target in multiple images. After the TCIs are detected from the input images, we could combine their positions in different images, thereby retrieving their relative positions to the survey vehicles. Based on these relative positions and the geolocation data of survey vehicles we collected using GPS and inertial methods, we can finally estimate the actual location of those assets. For example, each combination of two detections could generate a hypothetical location of the target asset, and the subsequent captures could result in clustered points around the physical position of that asset, followed by a clustering algorithm to extract that physical location (Hazelhoff et al., 2014a, 2014b, 2012).

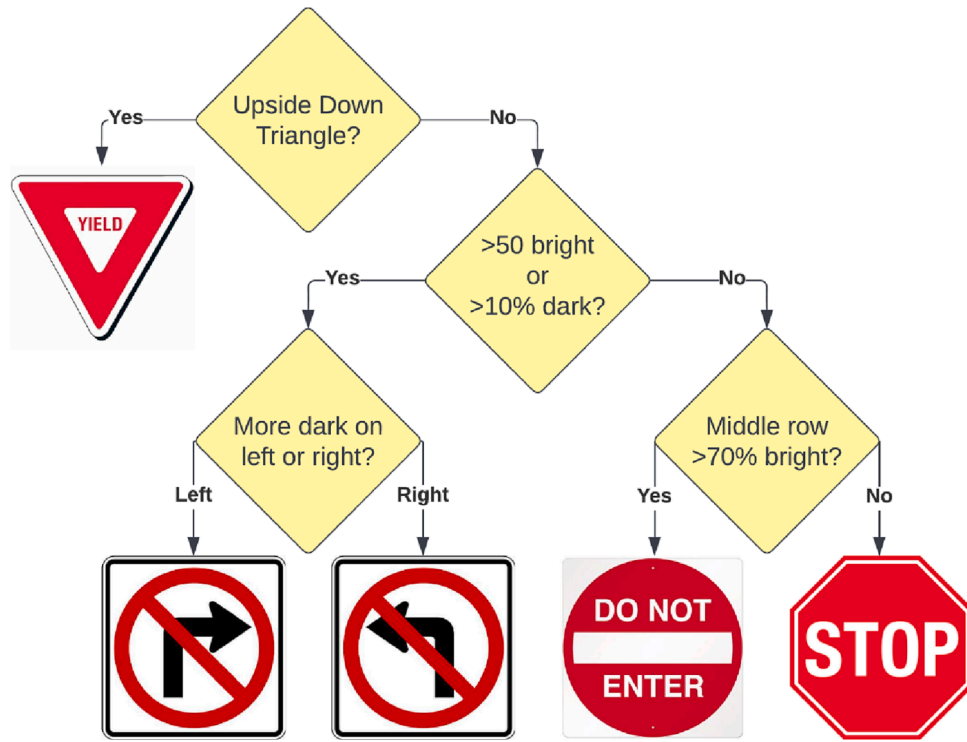


Fig. 3. Tree-based model in TCI classification (adapted from Haar and Safran, 2012).

### 3.4. Narrative review for TCI inventory establishment and management

#### 3.4.1. A general procedure for inventory establishment

To the best of our knowledge, there is no socially acknowledged process for building TCI inventory. In light of the the review findings, the workflow proposed by Nima Kargah-Ostadi could serve as an initial framework for roadway asset inventory governance. With the technology of Artificial Intelligence (AI), Cloud, and internal network, Nima Kargah-Ostadi's team raised a framework for automated inventory

establishment for roadway assets. As shown in Fig. 4, in Nima Kargah-Ostadi's method, the imagery data are collected using survey vehicles and the asset extraction and localization are accomplished at the same time with AI technology. After the data is collected and delivered to the office, it is uploaded to the central network or online cloud to share across different organizations. Through a quality control process conducted on a subset of the data, the TAM department could decide to accept or reject the established inventory (Kargah-Ostadi et al., 2020).

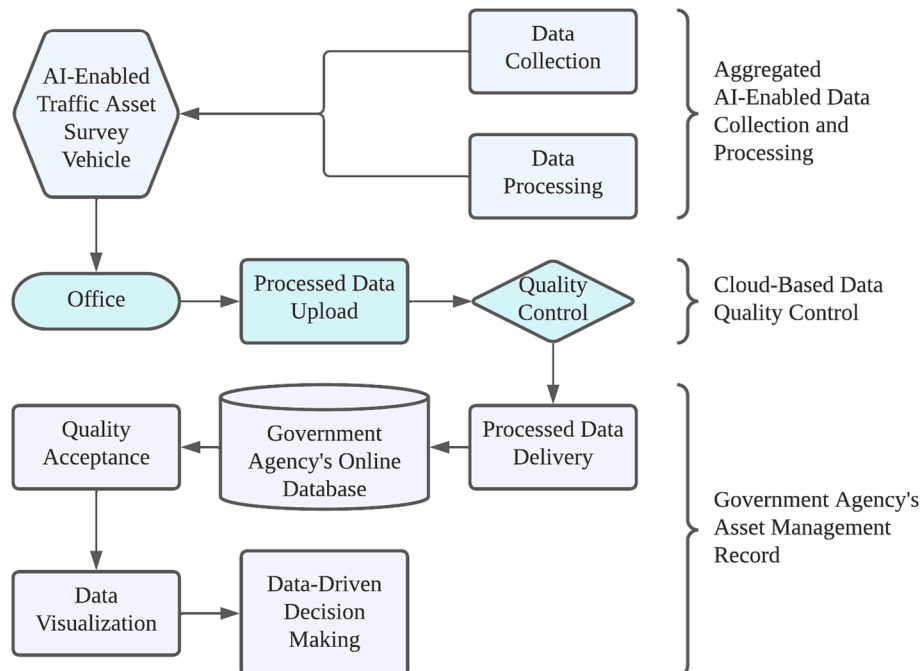


Fig. 4. Nima Kargah-Ostadi's framework for roadway asset inventory governance (adapted from Kargah-Ostadi et al., 2020).

### TCI inventory update

Inventory updates are conducted to maintain a baseline inventory, which contains the existing asset records in a certain study area and has been examined to be corrected. As illustrated in Fig. 5, when performing inventory updates, newly processed assets need to be compared with those in the baseline inventory one by one. If a newly digitized asset has the same type and location as the corresponding one in the baseline inventory, it would be labeled as “unchanged” in the baseline inventory (Strain et al., 2020). After the asset comparison, all assets would be classified into three categories: (1) unchanged signs, which have matched type and position with an existing sign in the baseline inventory; (2) removed signs, which exist in the baseline inventory but do not exist in the new digitized dataset; and (3) newly found signs, which are newly digitized but cannot match with any existing assets in the baseline inventory (Hazelhoff et al., 2014c). The inventory updates need to be completed in two modules: asset location match and asset type match.

**Asset location match:** A critical challenge in inventory updates is to compare the location of collected road assets. When the location of a newly inventoried asset doesn't match with the baseline inventory, it could imply a location change of the asset or a GPS positioning error. For example, researchers noticed that the position offset usually happens when the GPS signal is blocked by trees in forest areas or by high buildings in urban areas. GPS disturbances at a certain asset's position could lead to the position offset for a series of subsequent TCIs. Studies have demonstrated that the position offsets among these TCIs are generally uniform in the same area, which can be identified and corrected through the window detection method. For example, Hazelhoff et al. proposed a context-based drift correction by leveraging the positions of all neighboring traffic signs within a 150-meter buffer to correct the position offset for a newly detected sign (Hazelhoff et al., 2014a, 2014b).

**Asset type match:** Comparing the asset type along with the location is an important step in detecting changes or mutations in the new inventory. When comparing the newly inventoried assets with existing ones, if they are confirmed with the same asset type at the same location, they are considered matched assets. Please note that although TCIs of the same type usually have a similar appearance, small differences may still exist in some details. These minor differences may confuse the classification system and lead to a classification error. To prevent this kind of error, a cross-correlation of ideal templates of these asset types can be applied through the following procedure: (1) create a database of templates for each traffic asset type; (2) conduct a correlation analysis between each pair of asset type templates; the asset types with a correlation coefficient greater than a certain threshold would be considered as “similar type”; (4) When a newly inventoried asset is classified as a different type, researchers need to check if these two types are “similar type”. If they are, it would be considered as a match. Otherwise, the asset

type would be considered not matched, and the asset information would be updated (Hazelhoff et al., 2014a).

## 4. Discussion and conclusions

TCI systems are crucial in managing and directing traffic flows. The challenge of effectively developing and maintaining a comprehensive TCI inventory is a pressing concern for transportation agencies across the globe. This study aims to address this issue by employing a mixed review methodology to synthesize existing research and practices in the digitization and cataloging of TCIs. Initially, we conducted a Systematic Literature Review (SLR) to collate the predominant data sources and models used for TCI extraction and detection. Subsequently, we carried out a Narrative Review (NR) to gather the required modules and solutions essential for the construction and maintenance of a robust TCI inventory. Our research is the first to provide a comprehensive analysis of the entire workflow involved in establishing a TCI inventory by integrating advancements from various disciplines. This study offers a unique contribution to transportation agencies by delivering a valuable guideline for the creation and upkeep of TCI inventories. Simultaneously, it assists data scientists in comprehending the array of available data sources and computer vision techniques pertinent to the digitization and cataloging of additional road and urban assets.

### 4.1. Major findings for the TCI inventory establishment and management

The principal findings of this study address three specific research questions pertaining to TCI digitization and inventory development, including: (1) Which data types have been utilized for TCI digitization? (2) What methodologies have been employed for TCI digitization? (3) What procedures have been implemented for the establishment, maintenance, and updating of TCI inventories?

Concerning available data sources, this review reveals that the primary data for TCI digitization is typically collected through survey vehicles equipped with cameras, LiDAR, and GPS devices. This process yields two categories of data: TCI information and location. TCI information is predominantly derived from imagery data captured by cameras, which is particularly useful for traffic signs and lights. Meanwhile, LiDAR point clouds are more frequently employed for detecting road markings. GPS receivers, supplemented by inertial-based instruments or units, are generally used to gather TCI location data.

In terms of TCI digitization methods, data extraction typically involves three modules: detection, classification, and localization. Detection modules vary for imagery and LiDAR data. For imagery data, color-based and shape-based methods are the most commonly used for detection. Some studies combined color-based and shape-based methods to achieve a robust detection result. In contrast, LiDAR data first undergoes road surface extraction, followed by road marking extraction

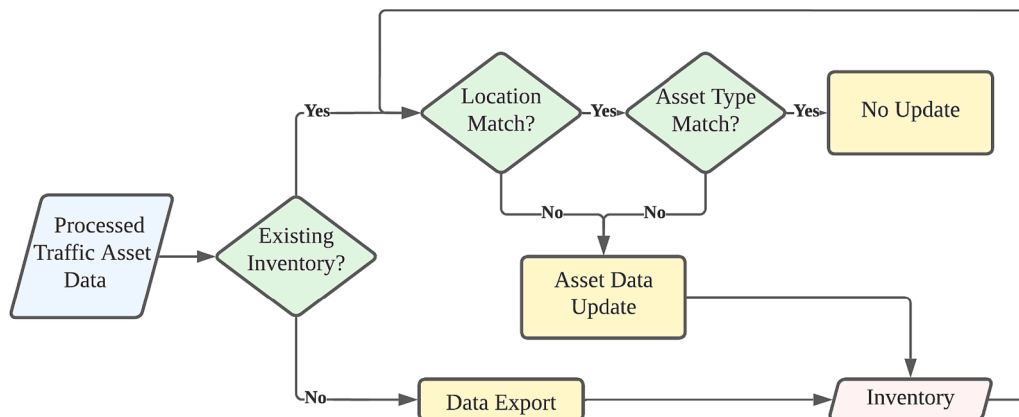


Fig. 5. Workflow for TCI inventory update.



based on the reflection intensity of points. To classify detected assets into their respective types, learning-based algorithms such as CNN and SVM are frequently employed. Some deep learning algorithms, like Faster R-CNN, SSD, and YOLO, can integrate detection and classification. To ascertain the actual locations of assets, GPS receivers and inertial-based instruments are typically integrated to derive the survey vehicle's location data, while imagery data can be utilized to estimate the relative position of targeted assets concerning the survey vehicle.

Following digitization and localization, the data must be submitted to TCI management offices or agencies for quality control. Once verified, the data can be used for new inventory establishment in the absence of existing inventory or for inventory updates and mutation detection when an inventory is already in place.

#### 4.2. Limitation in current TCI inventory management

Based on the review, we noticed the following limitations existed in current studies for an effective and reliable TCI inventory establishment in real-world settings. These can be summarized into two categories: data limitation and technique limitation.

##### 4.2.1. Limitation in data

Existing studies have reported two primary data limitations, encompassing data quality-related issues and a lack of benchmarks for model training.

Anomalies in TCI data present considerable challenges for the image-based detection and classification process in terms of reliability and accuracy. These anomalies primarily arise from two sources: the circumstances of targeted TCIs during data collection, such as extreme weather or environmental conditions, low visibility or noticeability, or improper positioning; and the condition of the TCIs themselves, including occlusion, damage, or deformation of the targeted TCI object. Images captured with these anomalies may lack sufficient information for interpretation, potentially leading to misclassification or failure to detect the targeted TCIs.

Data quality is another challenge for TCI extraction. For instance, motion blur can cause the weakening of sharp edges in captured frames, making it difficult to detect and classify TCIs. Image noise, manifesting as randomly distributed black and white pixels throughout an image, can significantly reduce the accuracy of TCI detection.

Regarding detection and classification methods, a reliable benchmark dataset for model training plays a critical role in ensuring model accuracy. As summarized in Table 5, only a few countries have well-established benchmark datasets for TCIs. Given the variability of TCI formats across countries, models trained on one country's benchmark dataset may yield different performance levels when applied to other countries.

**4.4.2.2. Limitation in techniques.** Accuracy in the detection, classification, and localization of road assets is crucial for TAM. However, the majority of existing studies concentrate on detection and classification accuracy, with the positioning accuracy of digitized TCIs being comparatively underexplored. Determining how to accurately map digitized TCI information remains a critical research question for future TAM and high-precision mapping endeavors.

Data redundancy and integration pose emerging challenges in TCI digitization. Numerous data sources and methods have been employed to digitize TCIs, leading transportation agencies and commercial companies to establish various TCI datasets. In future TAM, the amalgamation and integration of existing datasets with newly created ones to generate an updated TCI database will present a formidable obstacle. Moreover, inconsistencies among different inventories may exacerbate the difficulties associated with data integration.

Capturing and updating all pertinent information for TCI management continues to be a challenge. T. Nguyen et al. (2020) identified five

**Table 5**

Commonly used benchmark datasets for TCI detection.

Dataset Name	Regions	Sample Size	TCI Types	Reference
German Traffic Sign Recognition Benchmark	Germany	~52,000	sign	(KANG et al., 2018; Taki and Zemmouri, 2021)
German Traffic Sign Detection Benchmark	Germany	1,000	sign	(Pronchuk and Yakimov, 2018; Taki and Zemmouri, 2021)
KUL Belgium Traffic Signs Dataset	Belgium	13,444	sign	(Chen and Lu, 2016; Huang et al., 2017)
Laboratory for Intelligent & Safe Automobiles Datasets	California, US.	25,913	light	(Yu et al., 2018)
Swedish Traffic Signs Datasets	Sweden	3,488	sign	(Chen and Lu, 2016; Ellahyani et al., 2017)
Tsinghua-Tencent 100 K dataset	China	33,071	sign	(Yao et al., 2021; Zhang et al., 2020)
Stereopolis Database	France	251	sign	(Wali et al., 2015b)
RUG Traffic Sign Image Database	Netherlands	48	sign	(Mogelmose et al., 2012)
The Challenging Unreal and Real Environments dataset	N/A	1,719,900	sign	(Bousarhane et al., 2020)
Mapping and Assessing the State of Traffic InFrastructure	Croatia	~6,000 (TS2009), ~3,000 (TS2010), ~1,000 (TS2011)	sign	(Yuan et al., 2017)
WPI traffic light dataset	Worcester, USA	10,034	light	(Ouyang et al., 2020)
Bosch Small Traffic Light dataset	N/A	~13,300	light	(Pon et al., 2018)
Cyber Identity Biometrics Traffic Sign Dataset	N/A	690	sign	(Nuakoh, 2019)
DFG Traffic sign Dataset	Slovenia	6,957	sign	(Tabernik and Skocaj, 2020)
HERE map data	N/A		map	(Zhang et al., 2018)
International Cybernetics Corporation	N/A		roadway image	(Kargah-Ostadi et al., 2020)
Microsoft Common Objects in Context	N/A	200,000+	common objects	(Torres et al., 2019)
N/A	UK	1,200	sign	(Wali et al., 2019)
Russian Traffic Sign Dataset	Russia	80,000+	sign	(Safat B. Wali et al., 2019)
Spanish Traffic Sign dataset	Spain	615+	sign	(Ellahyani et al., 2021)
PASCAL Visual Object Classes	N/A	~3,000	visual objects	(Deng, 2019)

key elements that a successful road asset inventory should encompass: type, position, condition, installation date, and maintenance history. Nevertheless, existing research primarily focuses on TCI type detection and recognition, while studies on detecting road asset conditions remain

limited. Furthermore, an efficient TCI management system is required to record the installation date and maintenance history of TCIs for optimal management.

#### 4.3. Future work

To address the limitations and challenges identified, it is imperative to undertake further measures aimed at minimizing the impact of data quality and enhancing the performance of TCI detection and classification. One such measure includes employing efficient data pre-processing techniques to refine the quality of input data. Concurrently, additional efforts should be directed towards the establishment and enrichment of benchmark datasets for TCIs, which would foster the development of innovative solutions to mitigate the effects arising from a lack of benchmarks for model training and to augment classification accuracy. Furthermore, it is essential to devise a standardized, generalized procedure to facilitate TCI inventory establishment and maintenance. This, in turn, would not only streamline the process but also enable seamless data integration across diverse data sources and providers, thereby ensuring optimal efficiency and effectiveness in TCI inventory management.

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

#### Data availability

No data was used for the research described in the article.

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