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A Study of an Effective Continual Meta-Learning-Based Algorithm for Task-Specific and Device Characteristics Data in Traffic Management

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Abstract

Intelligent traffic management methods are gaining popularity for their potential to deal with a combination of both highly variable and constantly changing traffic environments, as well as a wide variety of sensors. However, there is growing interest in adaptive learning techniques that can handle changing traffic conditions and device-specific data features due to the complexity of traffic scenarios and the variety of sensor platforms.This paper provides a thorough analysis of continuous meta-learning-based methods for device-aware learning and task-specific adaptation in intelligent traffic management. The review looks at how meta-learning enables quick learning across a variety of traffic management tasks and how constant learning helps models retain previously learned information while adjusting to new traffic patterns.Additionally, the study examines current approaches to deal with data heterogeneity resulting from sensors, cameras, and Internet of Things (IoT) devices, emphasizing their effects on real-time performance, generalization, and model resilience. Based on learning frameworks, traffic applications, datasets, adaption methodologies, assessment criteria, and claimed performance, a comparative review of previous studies is presented.Catastrophic forgetting, domain adaptability across heterogeneous devices, limited benchmark datasets, computational complexity, and scalability for large-scale urban traffic networks are among the major issues that the paper highlights.A number of future research directions are discussed based on the results of the reviewed literature, including explainable artificial intelligence, federated learning, multi-modal sensor fusion for next-generation intelligent transportation systems, and continuous meta-learning integration with edge intelligence.This studyhighlights new prospects for creating adaptive, scalable, and robust intelligent transportation solutions while providing researchers and practitioners with an organized grasp of the current status of continuous meta-learning in traffic management.

Keywords: Intelligent Traffic Management, Meta-learning, Internet of Things, Machine Learning.

1. Introduction

The fast pace at which urban expansion is proceeding is the major reasonfor increasing congestion on the roads. Due to this [1], vehicles can be standing for a long time. Long-term standing impacts the environment through vehicle pollution, which delays emergency circumstances like accidents and causes human health-related problems associated with breathing that may be a life-threatening problem. Numerous other reasons besides growth contribute to traffic congestion; stopping development might not be the answer.The growing number of automobiles is one of the causes that can be addressed. Therefore, creating an intelligent system that can be used to lessen traffic congestion by addressing the number of vehicles is crucial [2].

To enhance traffic flow, reduce congestion, improving road safety, and optimizing route planning, Intelligent Transportation Systems (ITS) have emerged as a key element of contemporary smart cities [3].ITS is centered

on applications including intelligent traffic signaling, traffic flow prediction, accident detection, and dynamic route recommendation. Since it directly affects the effectiveness of traffic management and urban mobility planning, accurate traffic flow prediction is especially important [4].

Instead of depending on static training data, modern intelligent transportation systems need learning models that can continuously adapt to quickly changing traffic situations.Variations caused by peak-hour congestion, road construction, weather conditions [5], accidents, and special events demand adaptive learning mechanisms capable of maintaining high predictive performance over time. Traffic flow forecasting, congestion detection, incident identification, trip time prediction, and signal control optimization are just a few of the application-specific tasks that fall under the umbrella of traffic management [6]. Each of these tasks has unique data and learning requirements.Significant differences in data quality, resolution, sample frequency, and communication protocols are brought about by the growing use of heterogeneous sensing devices like surveillance cameras, IoT sensors, GPS-enabled cars, drones, and connected infrastructure [7].

These variations frequently result in domain shifts that impair traditional machine learning models' capacity for generalization. Continuous learning reduces catastrophic forgetting by allowing models to gradually pick up new information while retaining previously acquired knowledge [8].By enabling models to rapidly learn new traffic tasks from sparse observations through transferable information gained across similar tasks, meta-learning further improves flexibility.A potential framework for managing changing traffic conditions and varied device characteristics concurrently is provided by the integration of continuous learning and meta-learning.Recent research has shown how these adaptive learning paradigms can enhance computational efficiency [9], prediction accuracy, and robustness in a variety of intelligent transportation applications.As a result, ongoing meta-learning has become a crucial area of study for creating real-time, scalable, and robust traffic management systems that can support smart cities of the future.

Currently, a variety of technologies are being produced for advancement. These include fuzzy logic (FL), wireless sensor networks (WSNs), microcontrollers, machine learning (ML), and the Internet of Things (IoT), which are used to better control traffic in complex conditions.Environmental impact assessment [10], electronic toll collection, anomaly detection, unlawful activity identification, security monitoring, and traffic signal control systems are just a few of the numerous uses for ITMS.These ITMS applications are being used to efficiently enhance human quality of life issues and are gradually becoming an essential part of human life.

Aim and Objectives

To create and assess a meta-learning architecture for Intelligent Transportation Systems (ITS) that can quickly adapt to various traffic situations

Objectives

- To examine the shortcomings of current ITS prediction models based on machine learning in dynamic settings.
- To provide a framework based on meta-learning that allows for transferable and adjustable traffic prediction.
- To assess the suggested meta-learning model's performance using various datasets or traffic simulation situations.
- To evaluate the suggested method's capacity for generalization and transfer learning effectiveness.

Significance of the Study

With a focus on the use of meta-learning in non-stationary, real-world settings, this study adds to the expanding corpus of information on adaptive machine learning systems.Although meta-learning has been effectively used in fields like computer vision and few-shot learning, there is still little integration of it with ITS.By offering a framework designed for dynamic traffic conditions, the study overcomes this gap and offers new perspectives on adaptable AI for smart transportation.From an applied standpoint, the results of this study can assist smart city developers, traffic management authorities, and urban planners in putting more adaptable and durable ITS models into practice.Faster deployment across new cities, lower retraining costs, and better real-time adaptability to changing traffic circumstances are all possible with an ITS system powered by meta-learning. In the end, this results in less congestion, more efficient traffic flow, and more sophisticated urban mobility systems that can successfully react to unforeseen circumstances in the real world.

2. Related Works

Intelligent Transportation Systems and AI Integration

To increase mobility, lowering traffic, and enhancing general road safety, Intelligent Transportation Systems (ITS) have emerged as a crucial element of contemporary smart cities. Applications in traffic prediction, optimization, sensing, and control have been made possible by the incorporation of artificial intelligence (AI) into ITS [11].Loop detectors, GPS trajectories, and linked vehicle data are just a few of the data streams that AI-driven ITS systems use to produce predictive and adaptive reactions. By successfully simulating intricate spatiotemporal correlations in traffic data, recent developments in deep learning have completely transformed ITS [12].By detecting spatial connections between road segments, Convolutional Neural Networks (CNNs) have been effectively applied for traffic status estimation and flow prediction.Similar improvements in temporal pattern recognition for traffic forecasting have been demonstrated by Recurrent Neural Networks (RNNs), especially Long Short-Term Memory (LSTM) models.Additionally, by jointly learning spatial and temporal relationships, hybrid models that combine CNNs and LSTMs have been built to improve prediction accuracy.Despite these developments [13], the majority of deep learning models struggle to generalize outside of their training environment and rely on sizable, domain-specific datasets. Adaptive learning techniques that can sustain high performance in dynamic and varied traffic situations are necessary because of this restriction.Difficulties with Generalization and Adaptability Although AI-based ITS models perform admirably in certain situations, their flexibility in a variety of contexts is still restricted.The underlying data distribution is assumed to be steady in traditional supervised and reinforcement learning methods. However, due to time variations, regional diversity [14], and unforeseen events like accidents or weather fluctuations, data distributions in real-world traffic systems differ greatly.

Continual Learning

The ability to constantly learn from a series of tasks, possibly derived from a shifting distribution, is known as continuous learning. The main goal is to effectively learn new material while retaining previously acquired knowledge, avoiding the problem of forgetting earlier work.Traditional constant learning approaches frequently fail to explicitly address the meta-objective at the heart of meta-learning [15], despite the fact that both meta-learning and continual learning entail a distribution of tasks and seek to speed learning for new ones.Nonetheless, a potential paradigm for enhancing continuous learning is provided by meta-learning [16]. By integrating meta-objectives designed to improve ongoing learning, recent research has started to investigate this intersection.The gap between meta-learning and continuous learning systems is reduced by these meta-objectives, which are made to maximize the learning process and guarantee both rapid adaptation to new tasks and the retention of existing knowledge.

Challenges in Adaptability and Generalization

Although AI-based ITS models perform admirably in certain situations, they are still not very flexible in other contexts. The underlying data distribution is assumed to be steady in traditional supervised and reinforcement learning methods.However, due to time variations, regional diversity, and unforeseen events like accidents or weather fluctuations, data distributions in real-world traffic systems differ greatly [17]. These models' poor generalization to previously unexplored regions is a major drawback. Before being deployed in another city or season, models that have been stretched in one frequently need to undergo considerable retraining. Similarly, when the environmental dynamics are different from those observed during training, reinforcement learning techniques intended for traffic signal management show performance loss [18].Real-time adaptation is delayed, and computational costs are increased by this lack of transferability. Developing ITS models that can acquire more generalizable representations and quickly adapt to new contexts without requiring complete retraining thus represents a key research gap. Resolving this issue is essential to achieving context-aware, scalable ITS in smart cities.

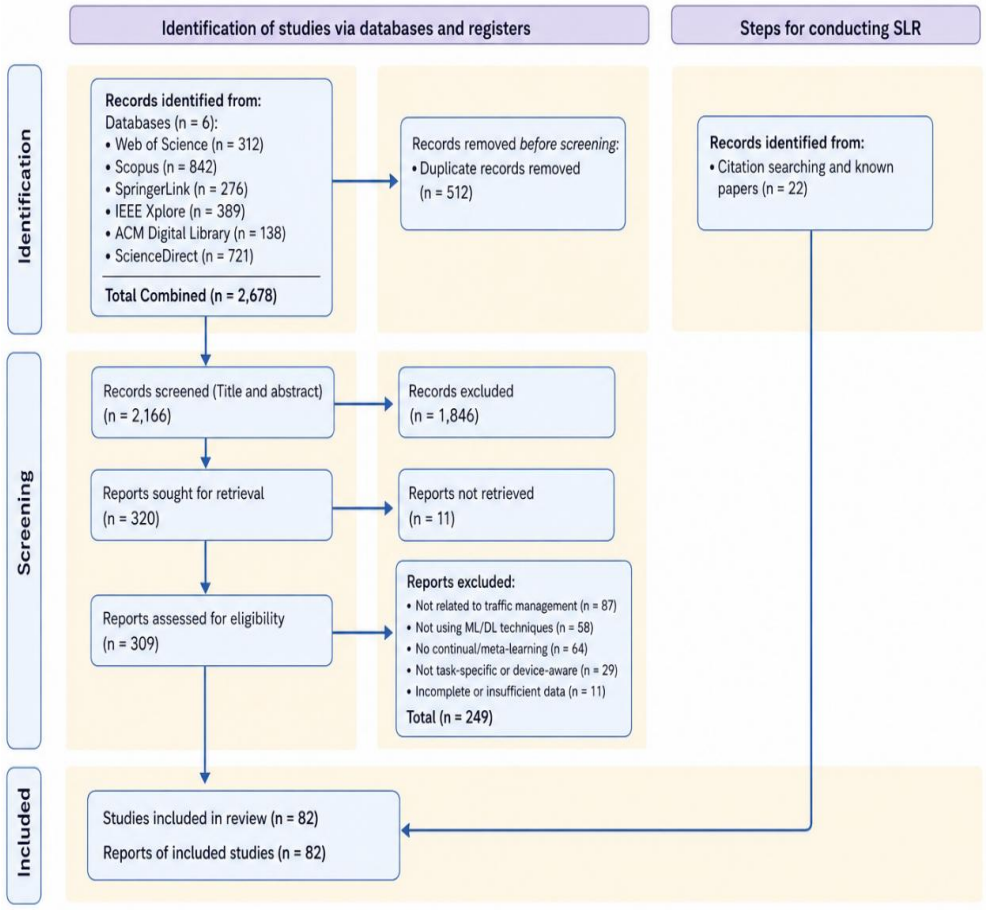
Meta-Learning in Dynamic Environments

Meta-learning is often referred to as "learning to learn," a novel paradigm in which models are trained to quickly adapt to new tasks with little input. Meta-learning algorithms seek to capture meta-knowledge, or patterns of how learning happens, that may be applied to a variety of tasks rather than just one.Model-Agnostic Meta-Learning (MAML), Reptile [20], and Prototypical Networks are well-known meta-learning algorithms that have demonstrated success in few-shot classification, robotics, and vision. These techniques guarantee quick adaptability to new data distributions by optimizing model starting settings.For example, Reptile uses first-order optimization to streamline the process, whereas MAML learns an initialization that enables effective fine-tuning

with just a few gradient steps [21]. Through the acquisition of transferable representations, meta-learning helps systems to manage domain transitions in dynamic situations.Meta-learning has been used in fields where context adaptation is crucial, like autonomous robotics, healthcare, and defect diagnostics. Meta-learning is positioned as a promising paradigm for handling the inherent unpredictability in ITS because of its versatility.

3. Methodology

The research approach employed in this study is described in detail in this section. In addition to producing systematic results, a systematic review is a professional approach to doing reliable research. Every step of the process, from developing research questions to reporting results, is rigorous, and the study is generally transparent. The steps and activities of the systematic review process are shown graphically in Figure 2, which gives a clear picture of the processes involved in this thorough review [22].



3.1. Review Protocol

To guarantee an open, methodical, and repeatable literature review procedure, the review was carried out in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) criteria.Based on predetermined selection criteria, PRISMA offers an organized framework for finding [23], screening, evaluating eligibility, and incorporating pertinent studies. Prior to the start of the literature search, the review protocol specified the research objectives, search method, inclusion and exclusion criteria, and quality assessment techniques.A multi-stage screening procedure was used to eliminate duplicate or unnecessary records once pertinent studies were acquired from large scientific databases. This procedure made sure that the final review contained only excellent and pertinent research on task-specific learning, continuous meta-learning, and device features in intelligent traffic management.

3.2. Literature Search Strategy

To find research on intelligent traffic management, task-specific learning, diverse device features, and continuous meta-learning, a thorough literature search was carried out [24].Peer-reviewed journal articles, conference papers, and review articles from respectable digital libraries were all included in the search

procedure, as shown in Table 3. To combine several search phrases and provide thorough search results, Boolean operators (AND, OR) were used.To ensure uniformity in the review procedure, only English-language publications were taken into account. In order to capture recent advancements in adaptive learning for intelligent transportation systems, the literature search concentrated on papers from 2019 to 2025.

Table 1. Literature Search Strategy

Item	**Description**
Search Period	2019–2025
Language	English
Document Types	Journal Articles, Conference Papers, Review Articles
Search Technique	Boolean Search (AND, OR)
Research Area	Intelligent Transportation Systems, Artificial Intelligence, Machine Learning

3.3. Review Objectives and Research Questions

The overall objective of the systematic literature review is to obtain an overview of recent approaches applied to solving the cold-start issue, mainly involving meta-learning models [25]. To clearly direct this exploration, research questions have been formulated as follows:

RQ1: What are the major continual learning and meta-learning approaches applied in intelligent traffic management?

RQ2: How are task-specific learning techniques utilized for different traffic management applications, such as traffic prediction, congestion detection, and signal control?

RQ3: What challenges arise from heterogeneous device characteristics (e.g., IoT sensors, surveillance cameras, connected vehicles), and how are they addressed in existing studies?

RQ4: Which datasets, evaluation metrics, and benchmarking strategies are most commonly used to assess continual meta-learning models in traffic management?

RQ5: What are the current research gaps, limitations, and future directions for continual meta-learning in intelligent traffic management?

This review's main goal is to thoroughly analyze current studies on continuous meta-learning techniques for intelligent traffic control. The review's objective is to examine how task-specific adaptation is supported by continuous learning and meta-learning approaches [26], as well as how they deal with the difficulties posed by varied device characteristics in traffic data.In order to determine their advantages and disadvantages, it also compares current approaches, datasets, assessment measures, and application domains. The assessment also looks into future technologies, unsolved problems, and current research trends that affect adaptive traffic management systems [27]. Lastly, the study offers future research avenues for creating intelligent, reliable, and scalable traffic management systems.

3.3. Database Selection

Several scientific databases were chosen based on their applicability to computer science [28], artificial intelligence, transportation engineering, and intelligent transportation systems in order to guarantee extensive coverage of high-quality articles, as given in Table 4.These databases offer thorough indexing and peer-reviewed publications with significant citation effect. Using several databases increases the literature review's completeness and lessens publication bias.The databases SpringerLink, Scopus [29], Web of Science (WoS), IEEE Xplore, and ACM Digital Library are among the literature sources used in this systematic literature review. These databases are renowned for their broad coverage of peer-reviewed publications and their ability to house excellent research articles across a range of disciplines.

Table 2. Selected Scientific Databases

Database	Research Coverage
SpringerLink	Gives users access to a large selection of book chapters, conference papers, and peer-reviewed articles in a variety of fields.
Scopus	Includes a wide range of scholarly publications, conference proceedings, and peer-reviewed journals that provide in-depth coverage of scientific literature.
Web of Science (WoS)	It is well-known for its stringent selection procedure, offers strong citation analysis tools, and contains excellent peer-reviewed research publications.
IEEE Xplore	Hosts peer-reviewed publications, conference proceedings, and technical standards with a focus on computer science, electrical engineering, and related subjects.
ACM Digital Library	Extensive resources for obtaining technical reports, conference proceedings, and peer-reviewed articles in computer science and related fields.

3.4. Search Keywords and Query Formulation

A list of pertinent keywords was created in order to make a comprehensive literature search for this systematic literature review easier [30]. The most pertinent studies were found by using the chosen keywords in search queries. Table 3 displays these keywords.

Table 3. Search keywords

Keyword Categories	Keywords
Primary Approach	"continual meta-learning", "continual learning", "meta-learning"
Application Domain	"traffic management", "intelligent transportation systems", "smart transportation", "urban traffic"
Task-Specific Learning	"traffic flow prediction", "congestion detection", "incident detection", "traffic forecasting", "signal control"
Device Characteristics	"heterogeneous devices", "IoT sensors", "traffic cameras", "connected vehicles", "edge devices", "sensor heterogeneity"
Learning Paradigms	"incremental learning", "lifelong learning", "few-shot learning", "transfer learning", "domain adaptation"
Related Technologies	"artificial intelligence", "machine learning", "deep learning", "graph neural networks", "reinforcement learning"
Performance Objectives	"knowledge retention", "catastrophic forgetting", "cross-device adaptation", "real-time prediction", "generalization"

Consequently, the following search query was created using the aforementioned terms.("continual learning" OR "meta-learning") AND ("traffic management" OR "intelligent transportation systems") AND ("IoT sensors" OR "traffic cameras" OR "connected vehicles").

These keywords and specified criteria, such as full-text availability and publications from 2019 to 2025, were utilized in the search query. Studies that directly overlap meta-learning, cold-start problems, and recommendation systems within the specified time frame were found by incorporating these terms into the search query [31].

3.5. Inclusion and Exclusion Criteria

To guarantee that only pertinent and excellent studies were included, predetermined inclusion and exclusion criteria were set prior to the screening procedure, as demonstrated in Table 6. Excluded were studies that had nothing to do with adaptive learning strategies or intelligent traffic management [32].

Table 6. Inclusion and Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
Published between 2019 and 2025	Published before 2019
English-language publications	Non-English publications
Peer-reviewed journals and conferences	Editorials, book chapters, theses
Focus on continual learning or meta-learning	Unrelated to traffic management
Studies involving intelligent transportation systems	Duplicate publications

3.6. Data Extraction and Quality Assessment

A consistent data extraction form was used to methodically obtain pertinent information from each chosen study. Publication details, study goals, learning strategies, traffic applications, datasets, performance measures, strengths [33], and limitations were all extracted. The methodological rigor and applicability of each study were further assessed using predetermined quality assessment criteria as given in Table 7.

Table 7. Key quality criteria

Quality Criteria	Description	Number of '1' Scores	Percentage of '1' Scores (%)
Quality-Q1	Is the research objective clearly stated?	74	92.50%
Quality-Q2	Is the methodology adequately described?	71	88.75%
Quality-Q3	Are the experimental results or findings clearly presented?	76	95.00%
Quality-Q4	Does the study provide valuable contributions to traffic management and continual meta-learning?	69	86.25%

3.8 Data Synthesis

To find patterns, similarities, discrepancies, and research gaps among the chosen studies, the retrieved data were combined using qualitative and comparative analysis methodologies. Based on learning methodology, traffic application, datasets, device characteristics, evaluation measures, benefits, and constraints [34], a comparative assessment was carried out. The combined results were utilized to pinpoint new lines of inquiry and prospects for ongoing meta-learning in intelligent traffic control.

4. Comparative Analysis of Existing Studies

In this section, the selected studies are compared in this part according to their learning strategies, application domains, datasets, device attributes, and assessment measures. In ongoing meta-learning for intelligent traffic management, the analysis identifies current research trends, strengths, limits, and gaps.

4.1 Comparison of Learning Approaches

A range of learning techniques, such as machine learning, deep learning, continuous learning, meta-learning, and hybrid frameworks, are used in the evaluated papers.Because of their strong predictive power, deep learning techniques dominate traffic prediction applications, but ongoing and meta-learning techniques have drawn interest for adaptive learning,as shown in Figure 2.Better information transfer and generalization across changing traffic scenarios are shown by hybrid models [35]. The comparison shows that intelligent transportation systems are increasingly adopting adaptive learning principles.

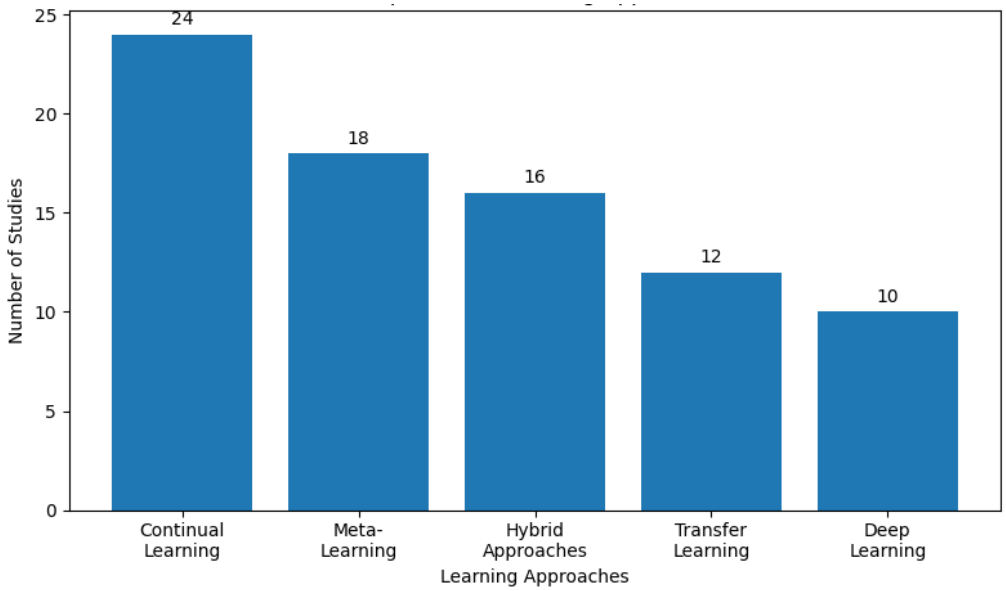


Figure 2. Comparison of learning algorithm

4.2 Comparison of Traffic Management Applications

Numerous traffic management applications, such as traffic flow prediction, congestion detection, incident detection, trip time estimate, and traffic signal optimization, are covered by the chosen research.Because of its importance in urban mobility planning, traffic flow prediction continues to be the application that has been studied the most. Intelligent incident detection and adaptive signal regulation using real-time data have been the focus of recent studies.The comparative research shows how AI-driven methods are becoming more widely used for a variety of traffic management activities, as illustrated in Figure 3.

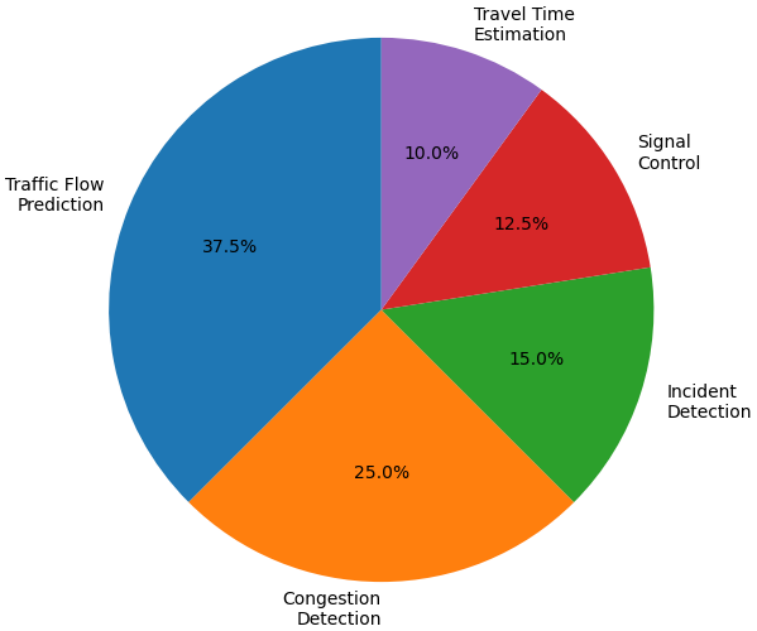


Figure 3. Comparison of Traffic Management Applications

4.3 Comparison of Datasets and Device Characteristics

The reviewed studies make use of both real-world traffic data gathered from heterogeneous sensing devices and benchmark datasets. Loop detectors, GPS-enabled cars, IoT sensors, surveillance cameras, and connected transportation infrastructure are examples of common data sources (Figure 4).Model performance is impacted by device heterogeneity, which introduces differences in data quality, sampling frequency, and communication

protocols. The analysis highlights the significance of strong learning strategies that can adjust to a variety of data features.

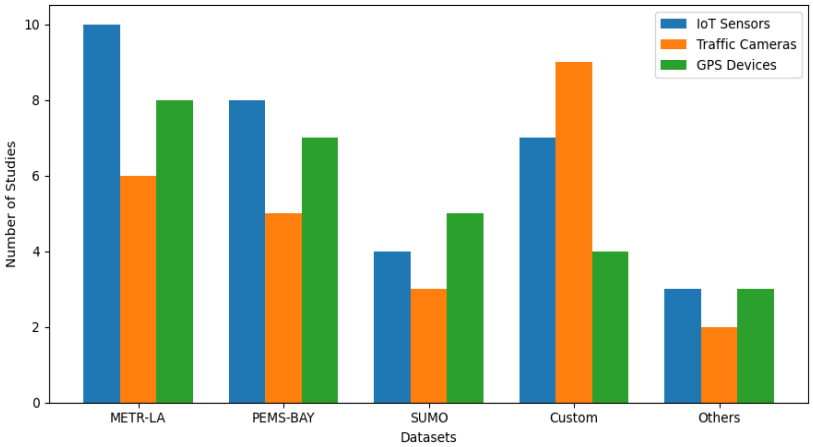


Figure 4. Comparison of Datasets and Device Characteristics

4.4 Comparison of Performance Evaluation Metrics

A range of classification and regression indicators is used to evaluate performance across the analyzed research (Figure 5). The metrics that are most commonly given are accuracy, precision, recall, F1-score, mean absolute error (MAE), and root mean square error (RMSE).The particular traffic management application and prediction task determine which assessment metric is used. Comparative evaluation of these indicators offers insightful information about the efficacy and resilience of current learning strategies.

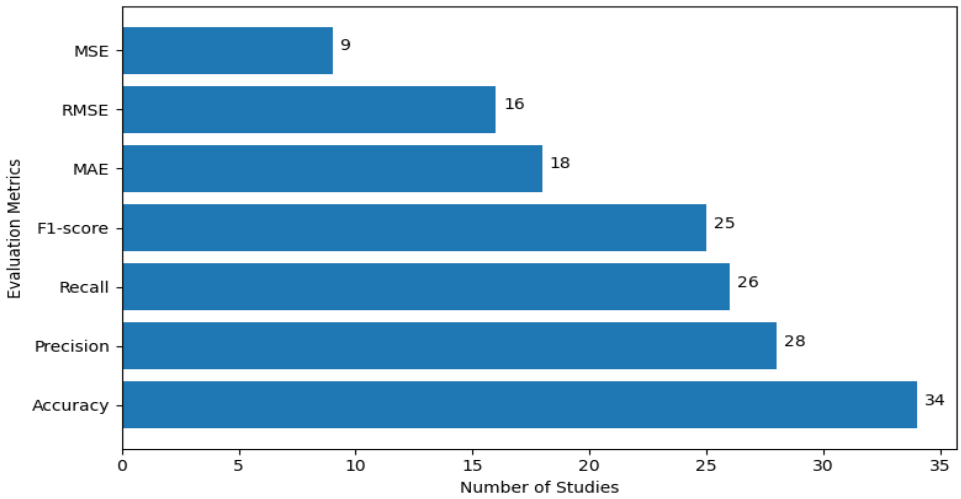


Figure 5. Comparison of Performance Evaluation Metrics

4.5 Strengths, Limitations, and Research Gaps

Adaptive learning techniques have greatly increased cross-task knowledge transfer and traffic prediction accuracy, according to the comparative analysis. Nevertheless, issues including restricted benchmark datasets, computational complexity, heterogeneous device integration, and catastrophic forgetfulness are still unsolved.Rather than integrating continual meta-learning frameworks, many current studies concentrate on individual learning paradigms. These results point to a number of directions for further investigation on intelligent, scalable, and adaptable traffic management systems.

4.6. Discussions

By facilitating adaptive learning across dynamic traffic scenarios and heterogeneous sensing equipment, continuous meta-learning has emerged as a potential paradigm for intelligent traffic management, according to the comparative analysis.Several issues, such as catastrophic forgetting, cross-device generalization, and

computational complexity, are still unresolved despite the fact that previous research shows gains in prediction accuracy, knowledge retention, and model flexibility.The results also show an increasing tendency toward the integration of meta-learning and continuous learning to support scalable intelligent transportation systems and real-time traffic applications.These findings show that in order to expedite future research and real-world implementation, consistent benchmark datasets, uniform evaluation frameworks, and effective adaptive learning models are required.

5. Conclusions

In this review, a thorough analysis of continuous meta-learning-based methods for device-aware learning and task-specific adaptation in intelligent traffic management. The review looks at how meta-learning enables quick learning across a variety of traffic management tasks and how constant learning helps models retain previously learned information while adjusting to new traffic patterns.Additionally, the study examines current approaches to deal with data heterogeneity resulting from sensors, cameras, and Internet of Things (IoT) devices, emphasizing their effects on real-time performance, generalization, and model resilience. Based on learning frameworks, traffic applications, datasets, adaption methodologies, assessment criteria, and claimed performance, a comparative review of previous studies is presented.Catastrophic forgetting, domain adaptability across heterogeneous devices, limited benchmark datasets, computational complexity, and scalability for large-scale urban traffic networks are among the major issues that the paper highlights.A number of future research directions are discussed based on the results of the reviewed literature, including explainable artificial intelligence, federated learning, multi-modal sensor fusion for next-generation intelligent transportation systems, and continuous meta-learning integration with edge intelligence.This studyhighlights new prospects for creating adaptive, scalable, and robust intelligent transportation solutions while providing researchers and practitioners with an organized grasp of the current status of continuous meta-learning in traffic management

The analysis also revealed several limitations in existing research, including catastrophic forgetting, limited benchmark datasets, high computational complexity, and insufficient integration of continual learning and meta-learning within unified frameworks. Although recent studies have reported encouraging results, there remains a need for more scalable, efficient, and robust adaptive learning models capable of supporting real-time intelligent transportation systems. Future research should focus on developing integrated continual meta-learning architectures, leveraging federated and edge intelligence, incorporating explainable artificial intelligence, and improving cross-device knowledge transfer using multi-modal traffic data. Overall, this review provides a comprehensive understanding of the current research landscape, identifies critical research gaps, and offers valuable insights that can guide future developments toward resilient, adaptive, and intelligent traffic management systems.

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