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EXPLORING AI FOR EFFECTIVE TRAFFIC PREDICTION AND MITIGATING URBAN TRAFFIC CHALLENGES - A RECONNAISSANCE

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Abstract

The rapid urbanization and rising population density in cities have significantly increased traffic congestion, leading to adverse effects on economic productivity, environmental sustainability, and quality of life. Accurate traffic prediction is crucial for mitigating these challenges and ensuring efficient transportation systems. Traditional traffic forecasting models often struggle with nonlinear traffic patterns, which has propelled the adoption of advanced artificial intelligence (AI) techniques, particularly machine learning (ML) and deep learning (DL). These approaches excel in processing large, dynamic datasets and capturing intricate spatial-temporal dependencies in traffic data.

Ensemble learning methods, which combine multiple ML and DL models, have emerged as a robust solution to address the limitations of individual models. Techniques such as bagging, boosting, and stacking enhance prediction accuracy by leveraging the strengths of diverse algorithms and mitigating errors. Recent advancements, including hybrid

models like CNN-LSTMs and attention-based frameworks, demonstrate significant improvements in forecasting complex urban traffic conditions.

This study thoroughly explores the application of AI-driven traffic prediction methodologies, emphasizing the potential of ensemble learning in overcoming challenges like data sparsity, scalability, and real-time demands. The outcomes of this exploration extend beyond traffic prediction to encompass critical areas of congestion management, pollution control, and road utilization. The integration of AI enables accident detection, dynamic routing, and public transport planning, contributing to safer and more efficient urban mobility systems.

By leveraging AI for smart city integration, this research also highlights its application in emergency services and weather impact analysis, ensuring robust responses to environmental and operational challenges. Reviewing state-of-the-art models and their integration into Intelligent Transportation Systems (ITS), this study provides a framework for sustainable urban mobility. The findings aim to guide researchers and practitioners in developing reliable, efficient, and scalable traffic management solutions, advancing smart city initiatives by enhancing transportation efficiency and reducing congestion.

Introduction

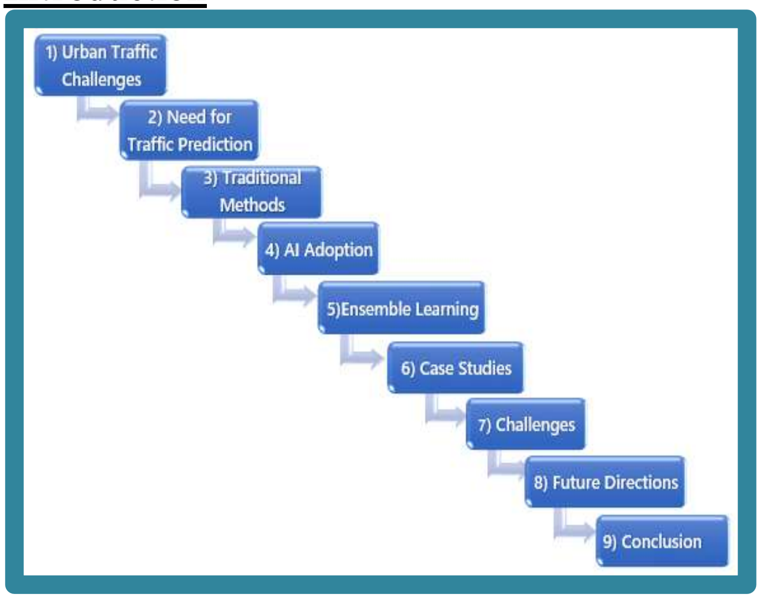

Fig. 1. Flow chart of the work done in this paper

Keywords: AI Traffic Prediction, Ensemble Learning, Sustainable Urban Mobility, Intelligent Transportation Systems (ITS), Smart City Traffic Management, Hybrid AI Models for Urban Transport, Real-Time Traffic Analytics

Urbanisation and the growing density of city populations have brought unprecedented challenges to transportation systems worldwide. Currently, 55% of the global population lives in cities, and by 2050, this figure is expected to increase by another 13% [1]. This trend not only amplifies traffic congestion but also escalates associated issues such as increased environmental pollution, a higher incidence of traffic accidents, and extended travel times [2, 3]. For instance, traffic congestion is estimated to cost the U.S. economy around $120 billion annually, underscoring the urgent need for effective traffic management solutions [4]. Traffic prediction has become a central focus of Intelligent Transportation Systems (ITS), as accurate forecasting of traffic flows can alleviate congestion, reduce vehicle emissions, and can help traffic stakeholders as shown in the following table, ultimately contributing to safer, more efficient, and sustainable urban environments [5].

The following table displays the various Traffic Stakeholder:

Category	Description
Decision Authorities	Responsible for designing and implementing traffic-related regulations and laws.
Commercial Entities	Organisations impacted by traffic flow, including delivery and logistics firms.
Data Providers	Agencies offering traffic data analytics and real-time updates.
Public Authorities	Entities overseeing infrastructure development and urban mobility strategies.

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Flow Supervisors	Professionals monitoring and controlling traffic flow in real-time.
City Developers	Experts strategizing sustainable urban layouts and road usage patterns.
Commuters	Individuals using roadways, including drivers, cyclists, and pedestrians.

Fig. 2: Benefits of traffic flow prediction

The development of Intelligent Transportation Systems (ITS) leverages advanced technologies, including communication, computation, and control, to enhance urban mobility and address traffic issues [6]. Central to ITS is the Internet of Things (IoT), which uses interconnected sensors and devices to collect real-time data on vehicle flow and speed, providing crucial insights for predictive models [7–9]. However, the spatial and temporal complexities of traffic data demand advanced models to handle dynamic, non-linear patterns effectively [10].

Traditional models like ARIMA have been used for short-term traffic forecasting but fall short in managing non-linear and stochastic traffic characteristics [11, 12]. This limitation has driven the adoption of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) techniques, which excel in capturing intricate spatio-temporal dependencies [13]. Techniques such as CNNs, RNNs, and LSTMs process large datasets for accurate predictions [14, 15], while newer models like T-GCRNN improve adaptability by utilizing graph structures for spatial and time-series data [16]. GRUs and attention-based models further enhance predictions by analyzing dynamic traffic patterns with spatio-temporal data from IoT devices [17, 18].

Emerging methods like Graph Convolutional Networks (GCNs) and Spatio-Temporal Graph Convolutional Networks (STGCNs) demonstrate significant advancements in modeling complex spatial relationships and support informed decisions for sustainable urban development [19]. This review evaluates AI, ML, and DL methodologies, emphasizing their strengths, limitations, and contributions to advancing smart cities through

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enhanced traffic prediction and management.

Background Study on Traffic Prediction As urban areas grow, traffic congestion has emerged as a significant challenge, impacting public health, environmental quality, and economic productivity. Intelligent Transportation Systems (ITS) have been developed to address these challenges by leveraging the Internet of Things (IoT) and data analytics for real-time traffic flow management. The goal of ITS is to establish interconnected, data-driven traffic systems capable of minimising congestion and improving urban mobility through precise traffic predictions (20). In recent years, artificial intelligence (AI) and its subfields—machine learning (ML) and deep learning (DL) as shown in Fig. 3 —have become central to these efforts, providing innovative approaches to forecast traffic conditions accurately.

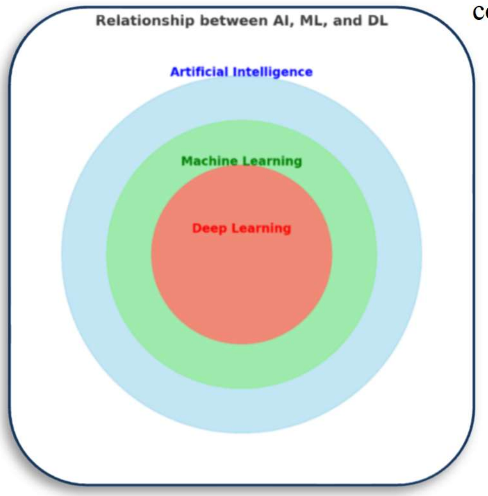

Fig.-3: AI and it's subfield

Traditional Approaches in Traffic Prediction Historically, traffic prediction relied on parametric models like the Auto-Regressive Integrated Moving Average (ARIMA) and Kalman filters, which analyse time-series data to predict short-term traffic flow. While these models are effective in capturing linear trends, their predictive accuracy can suffer with nonlinear and dynamic traffic patterns common in urban areas (21). Researchers have also explored hybrid approaches that combine traditional statistical techniques with ML to capture complex dependencies in traffic data. For instance, combining ARIMA with a Nonlinear Wavelet Neural Network has shown enhanced prediction accuracy under fluctuating traffic conditions (**Machine Learning Techniques for Traffic Prediction**

Learning Type	Algorithm Subtype	Examples
Supervised Learning	Classification	Decision Trees, Support Vector Machines
	Regression	Linear Regression, Polynomial Regression
	Ensemble Learning	Bagging, Boosting
Unsupervised Learning	Clustering	K-Means, Gaussian Mixture Model (GMM)
	Association	Apriori, Eclat
	Dimensionality Reduction	PCA (Principal Component Analysis), t-SNE

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Semi-Supervised Learning	Generative Models	Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs)
	Graph-based	Graph Convolution Networks (GCNs)
	Self-training	Self-Learning Algorithms
Reinforcement Learning	-	Q-Learning, Deep Q-Networks (DQN)
Multi-instance Learning	-	Bagging, Boosting
Inductive Learning	Deductive Learning	Neural Networks, SVMs
	Inductive Learning	Decision Trees, Covering Algorithms
Transfer Learning	-	Fine-tuning Pre-trained Models
Active Learning	-	Query-by-Committee, Uncertainty Sampling
Online Learning	-	Incremental Learning Algorithms
Multi-task Learning	-	Neural Networks for Joint Tasks
Ensemble Learning	Bagging	Random Forest, Bagging
	Boosting	AdaBoost, Gradient Boosting

ML techniques have proven highly effective in predicting traffic flow by identifying patterns in complex, nonlinear datasets. Common ML algorithms in traffic forecasting include Support Vector Machines (SVM), K-Nearest Neighbour (KNN), and Decision Trees (DT), each offering unique advantages based on data characteristics (23). SVM, for example, is valued for its capacity to manage high-dimensional data, making it ideal for traffic datasets with numerous features (24). KNN, a non-parametric method, is particularly effective when data lacks clear patterns or predefined clusters, making it useful for real-time traffic data with unpredictable variations (25). However, both methods

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encounter challenges when processing large datasets, as their performance can decrease with high-dimensional data and complex patterns.

Another widely used approach in ML for traffic prediction is the Random Forest (RF) algorithm, an ensemble method that combines multiple decision trees. RF has demonstrated robust accuracy and adaptability across various traffic datasets by minimising overfitting risks associated with individual decision trees, in addition, ML algorithms might be further subdivided into several sub-groups depending on distinct learning approaches, as shown in above table [26]. While ML techniques effectively address the challenges of nonlinear relationships, they often require significant computational resources, especially with large datasets collected from IoT sensors and real-time feed

Deep Learning in Traffic Prediction

The emergence of DL, particularly models like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks, has revolutionised traffic prediction by allowing systems to automatically learn and extract high-dimensional features from raw traffic data (27). CNNs excel at capturing spatial dependencies within traffic data, making them suitable for scenarios where geographical data impacts traffic flow (28). For instance, CNN-based models have been used to analyse traffic congestion patterns by processing data from adjacent road networks, effectively forecasting short-term flow variations across urban areas (29).

RNNs, including LSTMs, are designed for sequential data and have been widely adopted in time-series traffic prediction due to their capacity to model temporal dependencies (30). LSTMs, with their gated memory cells, overcome the issue of vanishing gradients in traditional RNNs, thus preserving long-term dependencies in traffic data. This ability makes LSTMs particularly useful for capturing day-to-day patterns and seasonal traffic fluctuations. However, despite their accuracy, LSTMs require significant computational power and long training times, which can be limiting for real-time applications (31)

Hybrid Models and Emerging Techniques

Hybrid models, which integrate multiple ML and DL techniques, have gained traction as they capitalise on the strengths of each approach. For example, combining CNNs with LSTMs allows a model to capture both spatial and temporal dependencies in traffic data, thereby enhancing prediction accuracy for complex urban traffic patterns (32). Additionally, recent studies have explored Graph Convolutional Networks (GCNs) for traffic forecasting, as these networks model the road network as a graph, capturing intricate spatial relationships that traditional models may overlook (33).

Another emerging approach involves attention-based models, which dynamically focus on relevant parts of the data to enhance prediction accuracy. Attention mechanisms have been successfully integrated with CNN and LSTM frameworks to improve predictive performance in urban traffic environments by prioritising critical sections of the traffic flow (34).

Importance of Traffic Flow Prediction in Smart Cities

Aspect	Description	References
Accident Occurrence Detection	Traffic flow prediction identifies high-risk congestion patterns, enabling real-time adaptive controls like dynamic speed limits to reduce collision risks.	【74】【75】
Pollution Control	Predictive traffic management lowers CO_2 and NO_x emissions by minimising idle times and optimising routes, contributing to sustainable urban environments.	【76】【77】

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Aspect	Description	References
Road Utilisation	Traffic prediction distributes vehicular loads across networks, preventing overuse of specific routes, reducing wear and tear, and extending infrastructure life.	【78】【79】
Time Management	Real-time predictions optimise travel times for commuters and enhance public transport scheduling, ensuring punctuality and reduced delays.	【80】【81】

ML Techniques for Traffic Flow Prediction

Problem	ML Techniques Used	Details	References
Accident Detection	Classification Algorithms	Support Vector Machines (SVM) and Decision Trees (DT) identify high-risk areas and accident patterns.	[82][83]
Pollution Control	Regression and Prediction Models	Linear regression models predict pollution levels based on vehicle density and optimise traffic flow to reduce emissions.	[84][85]
Road Utilisation	Reinforcement Learning	Reinforcement learning models balance road traffic distribution to prevent overutilization and reduce congestion on specific routes.	[86][87]
Time Management	Real-Time Prediction Models	Random Forest and k-Nearest Neighbour (k-NN) models optimise travel routes, ensuring reduced travel time for commuters and improved public transport schedules.	[88][89]

An ML model utilizing regression techniques and libraries like Pandas, Numpy, TensorFlow, and Scikit-learn predicted traffic data based on historical patterns, focusing on one-hour intervals using Kaggle datasets (2015–2017). While achieving accurate results, further research into deep learning and big data was recommended [35]. Q-learning, a reinforcement learning algorithm, optimized traffic light management in SUMO simulations by dynamically adjusting signals, showcasing its potential to address urban traffic challenges [36].

ML and DL methods, including Random Forest, Linear Regression, Stochastic Gradient Regression, Multilayer Perceptron Neural Networks, and RNNs, were applied for adaptive traffic light control, but DL methods outperformed ML models [37]. For lane change prediction, SVM achieved the highest accuracy using high-fidelity data from Peach Street, Atlanta, among four evaluated ML models [38]. A type-2 fuzzy logic system, leveraging backpropagation for coefficient updates, outperformed SVM and other fuzzy methods in short-term traffic prediction accuracy [39].

The Canonical Polygonal Tensor (CPT)-based approach reduced data requirements by decomposing historical traffic data and demonstrated superior accuracy compared to rolling average algorithms on the M62 motorway in England [40]. An intelligent monitoring system (ML-ITMS) combining SVM and RF achieved 98.6% prediction accuracy, optimized for LoRa networks [41]. GSA-ELM was employed for short-term traffic forecasting on Amsterdam motorways, achieving MAPEs below 12% [42].

ML methods were applied in Serbia using automatic traffic counters to predict traffic volumes effectively [43]. Gaussian Process Regression reconstructed traffic flows from travel times, though accuracy depended

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on high-quality input data [44]. In Tangier, Morocco, a hybrid ELM and ensemble model predicted hourly traffic while highlighting the importance of weather and road characteristics [45].

Various ML models like Naïve Bayes, Decision Trees, and SVM were tested in Bandung, Indonesia, revealing challenges like limited training datasets [46]. RF, SVR, Multilayer Perceptron, and Multiple Linear Regression were moderately successful in predicting urban traffic speed in Thessaloniki, Greece, with real-time accuracy limitations [47]. PCA and linear discrimination analyzed South African road accident data, yielding promising results with Naïve Bayes, Logistic Regression, and K-NN classifiers [48]. Finally, an ensemble-based regression framework converted traffic volume prediction into binary classification, effectively handling concept drift but struggling with spatial dependencies [49].

DL Techniques for Traffic Flow Prediction

Challenge	Deep Learning Technique	Implementation Details	References
Accident Detection	CNN-based frameworks	Processes traffic surveillance data to identify accidents based on patterns of abrupt vehicle behaviour changes and collision signals.	【90】 【91】
	Edge-based YOLOv8	Leverages edge computing to perform localised accident detection for rapid response in dense urban areas.	【92】 【93】
Pollution Control	Spatiotemporal LSTMs	Predicts and mitigates emissions hotspots by analysing spatiotemporal traffic data combined with vehicle pollution contributions.	【94】 【95】
	Reinforcement Learning Models	Optimises vehicle movement at traffic lights to minimise emissions caused by frequent stops and starts.	【96】 【97】
Road Utilisation	Transformer-based Traffic Models	Enhances road usage predictions by modelling congestion dynamics and redistributing traffic more evenly.	【98】 【99】
	Deep Graph Networks	Evaluates underutilised roads and redistributes traffic based on graph-based urban road topology analysis.	【100】 【101】
Time Management	Multi-task Learning Models	Integrates spatiotemporal inputs to optimise commuter travel time and public transport scheduling simultaneously.	【102】 【103】
	Convolutional LSTMs	Predicts real-time traffic flow and dynamically adjusts transportation operations to reduce delays.	【104】 【105】

A traffic prediction system using four Deep Learning (DL) approaches—Deep Autoencoder (DAN), Deep Belief Network (DBN), Random Forest (RF), and Long Short-Term Memory (LSTM)—estimated traffic flow in densely populated areas, focusing on parameters like zone type and weather, though dataset details were unspecified [50]. Neural networks predicted trip durations using K-Means clustering and Waze Live Map API data, with suggestions to include weather factors for better accuracy [51]. A Recurrent Mixture Density Network (MDN) combined RNN and density techniques for short-term prediction in Shenzhen, China, but dataset limitations hindered broader applications [52].

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An enhanced DBN improved traffic forecasting under adverse weather conditions by integrating highway and local monitoring data with Support Vector Regression (SVR) [53]. Urban traffic signals were optimized by integrating flow prediction and scheduling using real-world data from the Aliyun Tianchi platform [54]. The Traffic Congestion Index (TCI) model assessed congestion via SG-CNN, highlighting the need for external factors like weather for improved predictions [55]. Queue length prediction using LSTM neural networks and adaptive systems like InSync reduced overfitting through Sequential Model-Based Optimization (SMBO) [56].

The Attention-Based Multi-Task Learning (AST-MTL) model combined Fully Connected Neural Networks (FNN), Graph Convolutional Networks (GCNs), and Gated Recurrent Units (GRUs) for multi-horizon traffic predictions but required task-specific refinements [57]. The Feature-Injected RNN (FI-RNN) integrated temporal and contextual data for short-term forecasts, enhanced by sparse autoencoders, but suggested further feature extraction exploration [58]. Graph Convolution Networks analyzed spatial patterns for situational awareness, leveraging Caltrans PeMS data [59].

Hybrid models like LSTM-Graph-CNN effectively predicted congestion in the San Francisco Bay Area [60]. The Improved Bayesian Combination Model (IBCM-DL) addressed errors by integrating weather and accidents using Beijing highway data [61]. Recursive algorithms outperformed convolutional methods in traffic prediction using Floating Car Data, though data coverage was limited [62]. Deep ANN and CNN models forecasted traffic speeds under work zone conditions, emphasizing automation and data resolution for improvement [63].

CNN-LSTM hybrids analyzed spatial-temporal traffic patterns, suggesting additional data sources for scalability [64]. LSTMs corrected missing information for traffic jam predictions but needed optimization for low-speed areas [65]. The Deep and Embedded Learning Approach (DELA) faced challenges in explanatory power and embedded learning capabilities [66]. Integration of Big Data, DL, and in-memory computing enabled large-scale real-time forecasting with limitations in accuracy and dataset size [67]. Fuzzy CNN (F-CNN) enhanced flow prediction using uncertain accident information [68]. A GRU-based spatiotemporal model forecasted short-term traffic while excluding external factors like weather, limiting its scope [69].

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Ensemble Learning In Traffic Prediction

Technique	Description	Advantages	Common Applications in Traffic Prediction	References
Bagging (Bootstrap Aggregating)	Combines predictions from multiple models trained on bootstrapped datasets.	Reduces variance; handles overfitting well.	Short-term traffic flow prediction; travel time estimation.	[106]
Boosting	Sequentially trains models, giving more focus to misclassified instances.	Improves prediction accuracy; reduces bias.	Traffic congestion prediction; flow density analysis.	[107]
Random Forest	An ensemble of decision trees built using bagging and random feature selection.	High robustness to noise and overfitting.	Traffic speed estimation; traffic signal optimization.	[108]
Gradient Boosting	Combines weak models (e.g., decision trees) in a sequential manner using gradient descent.	Handles non-linear patterns effectively.	Traffic volume forecasting; anomaly detection in traffic patterns.	[109]
AdaBoost	Adjusts weights of misclassified samples iteratively to improve accuracy.	Simplicity; good for weak learners.	Predicting vehicle counts; road congestion alerts.	[110]
XGBoost	Optimized version of Gradient Boosting designed for speed and performance.	Fast computation; scalable to large datasets.	Real-time traffic monitoring; route optimization.	[111]
LightGBM	Gradient Boosting method optimized for large-scale data and lower memory usage.	Efficient for high-dimensional data.	Traffic flow prediction in smart city systems.	[112]

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CatBoost	Gradient Boosting method optimized for categorical features.	Handles categorical data effectively.	Prediction of traffic incidents based on categorical data.	[113]
Stacking	Combines multiple models' predictions as inputs for a meta-model.	Flexibility; leverages strengths of models.	Multi-modal traffic analysis; hybrid prediction models.	[114]
Voting (Hard/Soft)	Combines predictions from multiple models using majority (hard) or probabilities (soft).	Simple implementation; stable results.	Traffic state classification; travel time estimation.	[115]
Blending	Similar to stacking but uses validation data for meta-model training.	Simpler than stacking; avoids data leakage.	Combined short and long-term traffic flow prediction.	[116]

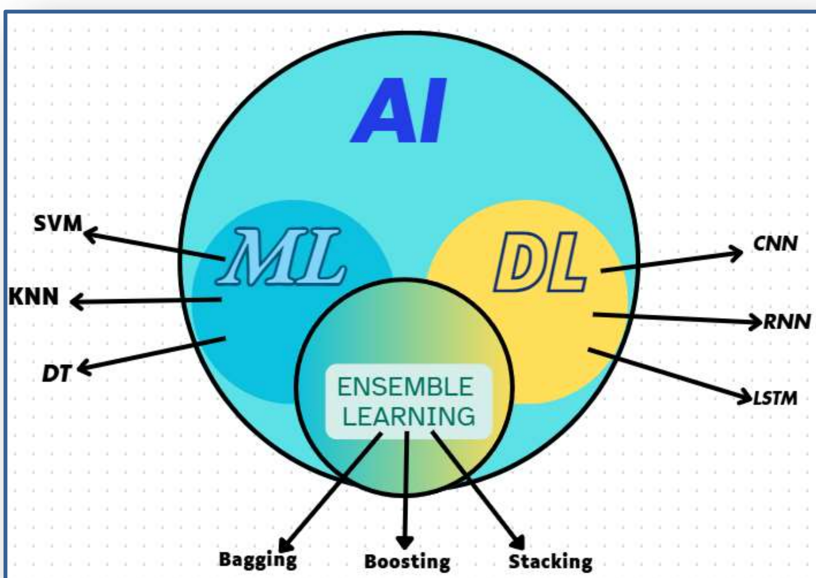

Fig-4: Ensemble Learning

Fundamentals of Ensemble Learning

Ensemble learning methods, which combine multiple individual models into a single predictive model, have gained significant attention in the field of traffic flow prediction due to their ability to leverage the strengths of diverse modelling approaches and improve overall prediction accuracy [70,129,130]. At the core of ensemble learning is the idea that by training multiple base models, each with its own unique strengths and weaknesses, and then combining their outputs, the resulting ensemble can make more accurate and robust predictions than any individual model could on its own.

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Applications of Ensemble Learning in Traffic Prediction

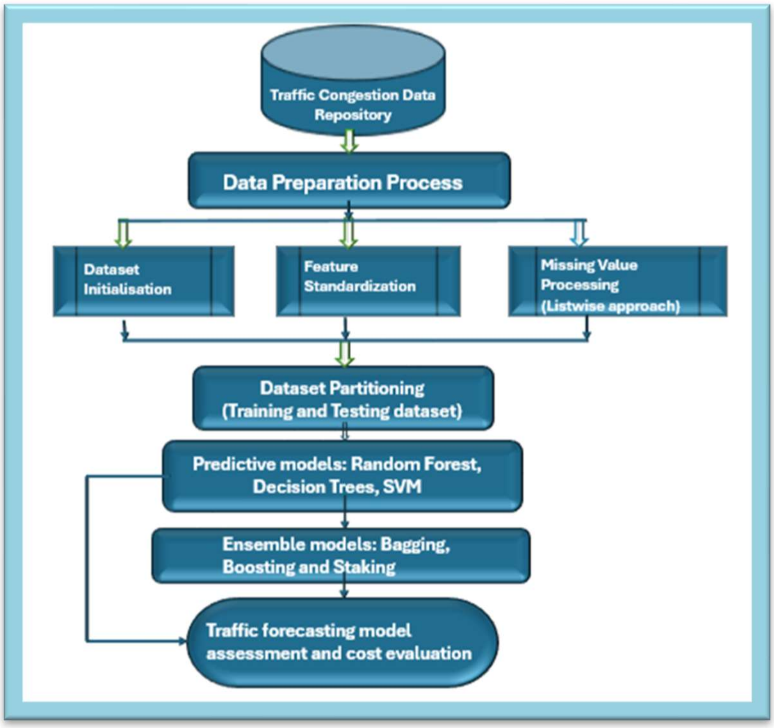

Fig. 5: Ensemble Learning in Traffic Flow Prediction

Ensemble learning has been extensively applied to the task of traffic flow prediction, with researchers exploring various combinations of base models and ensemble techniques. Traditional ensemble methods, such as **bagging**, **boosting**, and **stacking**, have shown promising results in improving the accuracy of traffic flow prediction models.**Ensemble techniques applied in traffic flow prediction:**A **joint temporal-spatial ensemble model** for short-term traffic prediction was proposed, combining historical and real-time traffic data to capture both temporal and spatial dependencies in traffic patterns [71].

More recently, the integration of ensemble learning with **deep neural networks** has further advanced the state-of-the-art in traffic flow prediction, as these hybrid approaches can effectively capture complex non-linear relationships in traffic data [70].

One approach, for example, involves using a **hybrid LSTM-CNN network** to model the heterogeneous interactions between different road agents, such as cars, buses, and pedestrians, and then combining the predictions from multiple such models to improve overall performance [72].

Another study presented a deep architecture for traffic flow prediction that learns deep hierarchical feature representations with spatio-temporal relations over the traffic network and then applies an **ensemble learning strategy via random subspace learning** to make the model more robust to incomplete data [73].

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COMPARISON TABLE SHOWCASING TRAFFIC PREDICTION ACCURACY USING MACHINE LEARNING (ML), DEEP LEARNING (DL), AND ENSEMBLE LEARNING METHODS, DERIVED FROM THE LATEST RESEARCH

Method	Technique Used	Dataset Used	Accuracy (%)	Advantages	Limitations	References
Machine Learning (ML)	Random Forest (RF)	PeMS	~76-82%	Effective for simpler data; interpretable results.	Struggles with non-linear temporal dependencies.	【117】【118】
	Gradient Boosting Machines (GBM)	PeMS	~78-84%	High precision for structured data.	High computational complexity for large datasets.	【119】【120】
Deep Learning (DL)	Long Short-Term Memory (LSTM)	METR-LA	~88-92%	Captures temporal dependencies effectively; good for sequential data.	Requires larger datasets and computational resources.	【121】【122】
	Graph Neural Networks (GNN)	METR-LA	~89-93%	Captures spatial dependencies across networks, outperforming other methods.	Challenging to train and requires extensive feature engineering.	【123】【124】
Ensemble Learning	Stacked LSTM and XGBoost	PeMS	~91-94%	Combines ML and DL strengths for improved accuracy and robustness.	Increased complexity and training time.	【125】【126】
	Voting-based Ensemble	METR-LA	~90-93%	Aggregates multiple models to reduce variance and bias.	Performance highly depends on base models used in the ensemble.	【127】【128】

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Exploring AI for Effective Traffic Prediction and Mitigating Urban Traffic Challenges for Future Research:

Focus Area	AI Techniques	Opportunities for Future Research	Benefits
Traffic Prediction	Neural Networks (e.g., LSTM, GNNs), Ensemble Models	Develop hybrid models for increased prediction accuracy.	Enhanced road safety, reduced congestion, and efficient traffic flow.
Congestion Management	Reinforcement Learning, Deep Q-Networks	Integrate multi-agent systems for adaptive traffic light control.	Minimises delays and optimises urban traffic networks.
Pollution Control	Decision Trees, Gradient Boosting	Utilise AI to predict pollution hotspots and propose eco-routing solutions.	Improved air quality and reduced environmental impact of traffic emissions.
Road Utilisation	Spatiotemporal Models, K-Means Clustering	Leverage geospatial AI for optimal road usage planning.	Prevents overuse of infrastructure and extends road longevity.
Accident Detection	Computer Vision (CNNs), Bayesian Networks	Develop real-time accident prediction and reporting systems.	Promotes quicker response times and enhanced road safety.
Smart City Integration	IoT + AI Models	Combine IoT sensor data with predictive models for real-time optimization.	Facilitates seamless smart city operations and enhanced urban planning.
Dynamic Routing	Ensemble Learning (Bagging, Boosting)	Introduce context-aware AI models for route adjustments during peak hours.	Reduces travel time and fuel consumption for commuters.
Public Transport Planning	Predictive Analytics, ARIMA Models	Create AI systems to optimise bus and train schedules dynamically.	Improves reliability and user satisfaction with public transport systems.
Emergency Services	Support Vector Machines, RNNs	Enhance routing for ambulances and fire trucks using predictive modelling.	Faster emergency response times and reduced fatality rates.
Weather Impact Analysis	Deep Learning Ensembles	Integrate weather prediction with traffic forecasting for better resilience.	Mitigates risks of weather-induced disruptions and accidents.

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Conclusion: This comprehensive survey underscores the transformative role of Artificial Intelligence (AI) in addressing the multifaceted challenges of urban traffic management. By delving into traditional, machine learning (ML), deep learning (DL), and ensemble learning methodologies, it highlights their strengths, limitations, and practical implications.

Key issues explored include the inadequacy of traditional methods like ARIMA in managing the non-linear and dynamic nature of urban traffic. Advanced ML and DL models, such as Long Short-Term Memory (LSTM) networks, Graph Neural Networks (GNNs), and hybrid CNN-LSTM frameworks, offer significant improvements in predicting complex spatial-temporal traffic patterns. Moreover, ensemble methods like Bagging, Boosting, and Stacking demonstrate their efficacy in combining the predictive strengths of individual models, achieving enhanced accuracy and robustness.

The paper also addresses critical urban traffic challenges such as accident detection, pollution control, efficient road utilization, and time management. AI-driven solutions like CNN-based accident detection frameworks, spatiotemporal models for emission prediction, and reinforcement learning for adaptive traffic signal control are highlighted as pivotal innovations for smart cities.

However, significant challenges persist, including computational demands of DL models, scalability issues in ML, and the complexity of ensemble methods. Future research directions include integrating IoT with ensemble models for real-time adaptability, developing hybrid ML-DL approaches to refine scheduling and travel-time predictions, and employing GNNs for comprehensive urban traffic network optimization.

In conclusion, this work not only advances the state-of-the-art in traffic prediction but also lays a foundation for future innovations in sustainable urban mobility. It serves as a vital resource for researchers and practitioners, aiming to create smarter, more efficient, and resilient urban transportation systems. By embracing AI, cities can move closer to achieving their smart city visions, ensuring enhanced mobility and quality of life for their inhabitants.

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