ENHANCING TRAFFIC FLOW AND SAFETY IN INTELLIGENT TRANSPORTATION SYSTEMS USING MACHINE LEARNING

Thesis Submitted
In Partial Fulfilment of the Requirements for the Degree of

MASTER OF TECHNOLOGY

in

Data Science

by

Prabhat Ranjan
(2K22/DSC/10)

Under the Supervision of

Dr. Abhilasha Sharma
(Asst. Professor, SE, DTU)

To the
Department of Software Engineering
DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Shahbad Daulatpur, Main Bawana Road, Delhi-110042, India

May, 2024

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)
Shahbad Daulatpur, Main Bawana Road, Delhi-42

CANDIDATE'S DECLARATION

I Prabhat Ranjan hereby certify that the work which is being presented in the thesis entitled Enhancing Traffic flow and safety in Intelligent Transportation Systems using Machine learning in partial fulfilment of the requirements for the award of the Degree of Master of Technology in Data Science, submitted in the Department of Software Engineering, Delhi Technological University is an authentic record of my own work carried out during the period from August 2022 to May 2024 under the supervision of Dr. Abhilasha Sharma.

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute.

Prabhat Ranjan

Candidate's Signature

This is to certify that the student has incorporated all the corrections suggested by examiners in the thesis and the statement made by the candidate is correct to the best of our knowledge.

Abhilasha Sharma

Signature of Supervisor (s)

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)
Shahbad Daulatpur, Main Bawana Road, Delhi-42

CERTIFICATE BY THE SUPERVISOR(s)

Certified that **Prabhat Ranjan** (2K22/DSC/10) has carried out their research work presented in this thesis entitled **"Enhancing Traffic flow and safety in Intelligent Transportation Systems using Machine learning"** for the award of **Master of Technology** from Department of Software Engineering, Delhi Technological University, Delhi, under my supervision. The thesis embodies results of original work, and studies are carried out by the student himself and the contents of the thesis do not form the basis for the award of any other degree to the candidate or to anybody else from this or any other University/Institution.

Abhilasha Sharma

Place: Delhi
Date: 27/05/2024

Dr. Abhilasha Sharma
Asst. Professor
Dept. of Software Engineering, DTU

Enhancing Traffic Flow and Safety in Intelligent Transportation Systems Using Machine Learning

Prabhat Ranjan

ABSTRACT

The increasing complexity and volume of urban traffic demand innovative solutions to enhance flow and safety, which are critical to the functionality and sustainability of modern cities. This thesis explores the integration of machine learning (ML) into Intelligent Transportation Systems (ITS) to address these challenges, presenting a multifaceted approach to improve decision-making processes within traffic management systems. By leveraging advanced machine learning models, this research aims to transform traditional ITS into dynamic systems capable of predictive and real-time responses to traffic conditions.

The research is structured around the development and implementation of four machine learning models, each designed to target specific aspects of traffic management. The first model utilizes Support Vector Regression (SVR) for traffic prediction, focusing on accurately forecasting traffic volumes and patterns to preemptively manage congestion and optimize traffic flow. The second and third models enhance the detection capabilities of ITS; an ensemble of YOLO-NAS and Mask R-CNN is developed for precise traffic light detection, and a combination of YOLOv8 and Detectron2 is employed for robust traffic sign detection. These models ensure accurate and reliable recognition of traffic controls, which is crucial for the safety and efficiency of both manual and autonomous vehicular navigation. The fourth model integrates Feedforward Neural Networks (FNN) with Long Short-Term Memory (LSTM) networks to predict traffic accidents, aiming to significantly reduce their likelihood by identifying potential risk factors and accident hotspots in real-time.

Each model undergoes a rigorous process of data acquisition, preprocessing, and evaluation, ensuring the robustness and reliability of their predictions. The models are trained on extensive datasets that include a variety of traffic scenarios, from which they learn to discern complex patterns and anomalies. The ensemble approaches, in particular, demonstrate superior performance in terms of accuracy and reliability, outperforming standard single-model systems in detecting and responding to traffic conditions.

The outcomes of this research demonstrate a substantial improvement in traffic flow and safety, showing the potential to notably reduce congestion and accidents in simulated environments. These enhancements are pivotal for the advancement of smarter, more responsive transportation systems, which are essential for improving the efficiency and safety of urban mobility.These improvements are critical for the development of smarter, more responsive transportation systems, which not only

enhance commuter safety but also contribute to the overall sustainability of urban environments by reducing emissions and improving the efficiency of road networks.

In conclusion, this thesis provides a comprehensive demonstration of how machine learning can be effectively integrated into ITS to address the challenges of modern traffic management. The successful implementation of these models showcases the potential of ML to revolutionize ITS by making them more adaptive, predictive, and efficient. Future work will focus on scaling these solutions to different urban settings, enhancing real-time data processing capabilities, and exploring the integration of additional ML models to further refine the responsiveness and accuracy of ITS. This research underscores the transformative potential of machine learning in fostering safer, more efficient urban transportation landscapes.

ACKNOWLEDGEMENT

I would like to express my deep appreciation to **Dr. Abhilasha Sharma**, assistant professor at the Department of Software Engineering, Delhi Technological University, for her invaluable guidance and unwavering encouragement throughout this research. She is one of the most generous persons I have ever known and she helped me in every step of the way during this enjoyable journey as a master's student. This work could not have happened the way it has without the contributions and perspectives from her. Here at Delhi Technological University, I have had some friends that I am thankful to be around. They made me feel truly at home. In particular, I would like to thank Vaibhavi who I had such a great time with. Last two years were great with such a lovely bunch of people around me. I would like to extend my sincere gratitude to the teachers and other staffs in software department for their teaching and mentoring efforts.

I would like to dedicate this thesis to my elder brother, Pawan who has been such a huge source of inspiration for me. This piece of work is for you.

Of course, my family supported me at every step of the way. My parents and brother have been instrumental in my success. Anything I do is for them.

Prabhat Ranjan
2K22/DSC/10

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVATIONS

ITS	Intelligent Transportation System
SVR	Support Vector Regression
LSTM	Long Short-Term Memory
YOLOv8	You Only Look Once Version8
YOLO-NAS	You Only Look Once Neural Architecture Search
GPS	Global Positioning System
ML	Machine Learning
SVM	Support Vector Machine
RCPM	Rear-end Collision Prediction Model
VGRAN	Variational Graph Neural Network
DITLCS	Dynamic Intelligent Traffic Light Control System
ASTGCN	Attention-Based Spatial-Temporal Graph Convolutional Network
RNN	Recurrent Neural Network
CNN	Convolutional Neural Network
TIS	Traffic Information Systems
PSNR	Peak Signal-to-Noise Ratio
ADAS	Advanced Driver Assistance System
IoU	Intersection Over Union
R-CNN	Region Based Convolutional Neural Network
Mask R-CNN	Mask Region Based Convolutional Neural Network
SSD	Single Shot Detector
GTSRB	German Traffic Sign Recognition Benchmark
STSD	Swedish Traffic Sign Dataset
ITSD	Indian Traffic Sign Dataset
BTSD	Belgium Traffic Sign Dataset
R-FCN	Region Based Fully Convolutional Network
AUC	Area Under Curve
XGBoost	eXtreme Gradient Boosting
LISA	Laboratory for Intelligent and Safe Automobiles

FNN	Feed-Forward Neural Network
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
NHAI	National Highways Authority of India
Faster R-CNN	Faster Region-Convolutional Neural Network
ASTGCN	Attention Based Spatial-Temporal Graph Convolutional Networks
MSE	Mean-Squared Error
Bi-LSTM	Bidirectional Long Short-Term Memory

CHAPTER 1

INTRODUCTION

1.1 Brief Overview

The purpose of the Intelligent Transportation System development is to take further steps in facing the growing challenges relating to urban mobility, traffic congestion, and road safety. Development of intelligent machine learning technologies in the field of traffic control and road safety goes beyond the boundaries of innovation in this area [1]. This paper takes into consideration the application of advanced machine learning models for the optimization of the flows of movement and road safety in urban transportation networks, which can make them smarter and more effective.

Moreover, there are so many areas for optimization that the intersection of transport and technology reveals. Classic traffic management and accident prevention schemes are overwhelmed by the demands enforced by modern infrastructure and the increases in population [2]. In this sense, dynamic and adaptive solutions are needed—those that can fully benefit from real-time data not only while making a direct decision but also over long-term traffic planning [3].

This research integrates and tests a wide variety of machine learning techniques in ITS to help combat difficult situations, particularly in the congestion modes, accident prediction, traffic sign recognition, and traffic light detection. In this context, this thesis tries to explain how machine learning can greatly outdo normal traffic management systems using models such as supported vector regression or SVR, LSTM systems, and very sophisticated ensemble approaches that integrate YOLOv8 and Detectron2.

This dissertation will detail how running such models over different datasets and real-life conditions is carried out. It gives a full-fledged analysis of which model is applicable in traffic flow and safety improvement. Individual models were selected because of handling a large amount of information and learning complex pattern recognition. Moreover, perturbations have to be taken into account with accurate model predictions.

So, in this respect, systematic analysis of such machine learning techniques will be pursued to outline practical applications of these technologies in ITS and hereby point out how it can mark an impact on the overall sustainability and safety within urban transportation. For that, creating a basis for further research and in principle providing how intelligent systems could be designed and implemented is found so that it manages to deal with any traffic-related problems ensuring that urban environments are safeguarded effectively and efficiently [4].

In a nutshell, the thesis aims to make important contributions to the state of the art in the field of intelligent transportation systems by showing the effectiveness of machine learning techniques in tackling some of the most critical problems that face traffic control and road safety nowadays [5]. This has been actualized by putting it at the very front line of advances in technology for transport.

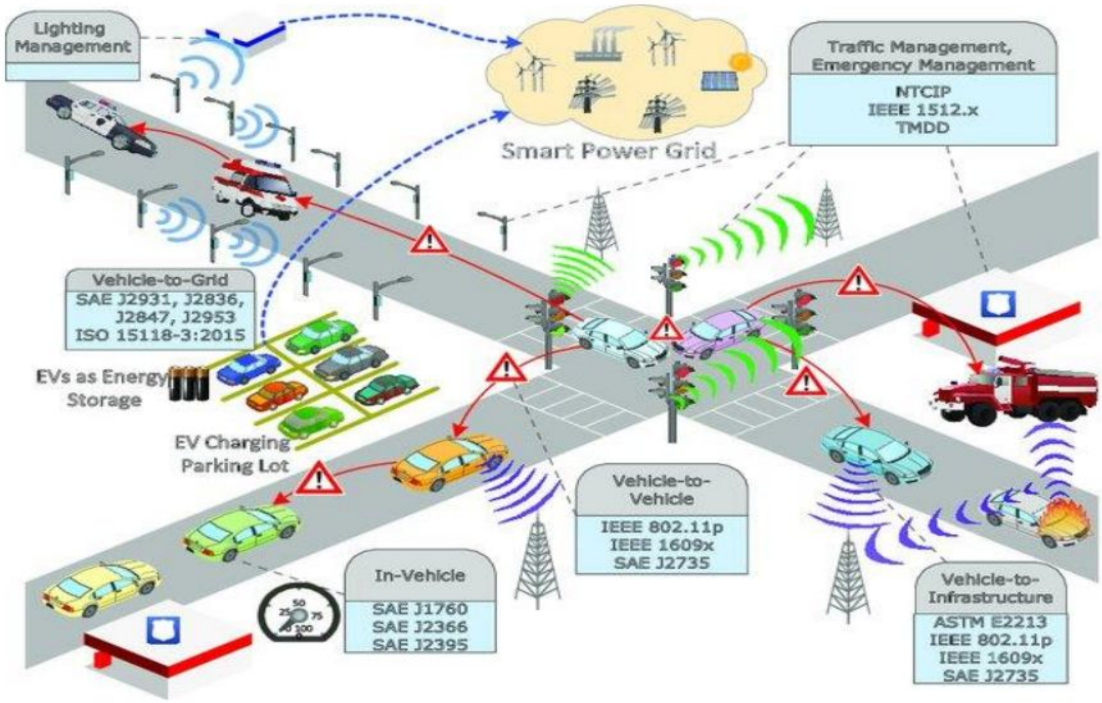


Fig. 1.1 Intelligent transportation system [6]

1.2 Motivation

This thesis comes as a result of the dire need for better traffic management and safety concerns in fast-growing urban centers. With continuous expansion of urbanized cities, traffic jam has become yet another growing concern, as well as road accidents, which are still a great challenge to economic effectiveness and public security [7]. ITS, meanwhile, point toward a critical next advance in addressing these issues, but conventional methods of ITS implementation have emerged as inherently incapable of dealing with the complexity and dynamism of contemporary urban traffic [8]. This is what drives the current thesis: machine learning holds the potential to revolutionize such systems, providing solutions that are subsequently more adaptive, efficient, and safe.

The conventional traffic management systems, too often unable to handle variability and unpredictability in the contemporary traffic flow yield, have been further exposed with increased traffic volumes globally [9]. Classic systems are deficient in predicting and solving traffic issues proactively because of the inability to analyze large chunk data from multichannel sources in real time [10]. In this context, new approaches must be urgently sought for handling and meeting the demands imposed by modern traffic systems.

Machine learning, on the other hand, is likely to bear a promising solution to the mentioned challenges through its learning on big data and improvement of accuracy with time. For this reason, since conditions keep changing, machine learning is fit for application on intelligent transportation systems [11]. This research will provide a platform for machine learning models in the analysis of patterns for the flow of traffic, prediction of possible congestion and accidents while in the act, and, in turn, relay actions that should be taken in real time to both traffic controllers and autonomous vehicles [12]. Incorporation of such technologies into ITS has the potential to dramatically reduce congestion and improve road safety levels, provide better flow of traffic, and decrease adverse environmental impacts due to lower emissions.

More so, machine learning in ITS is in line with what is happening throughout the world whereby smart cities are being computerized to use data and technologies to optimize municipal operations to enable economic development [13]. While improvements in the capabilities of ITS with machine learning support that vision, it directly translates into creating safer, more efficient urban environments [14]. This thesis will aim to research and evaluate the use of multiple machine learning models with respect to ITS. Hence, it contributes to the broader domain associated with infrastructure management and urban planning.

This research will, however, be limited to the above-identified areas in an attempt to demonstrate practical benefits of machine learning toward improvement in the level of capacity and associated security of transportation networks. This project ultimately aims to understand profoundly how such technologies could best be used within intelligent transport systems to overcome existing limitations and future challenges, thus rendering transportation systems more resilient and responsive.

1.3 Problem Formulation

The rapid proliferation of vehicles and massive urban expansions bring with them unprecedented traffic management challenges. Such traffic challenges become more complex, given that most of the traditional ITS have been found not to measure up to the dynamic character of urban traffic flows. Day by day, traditional strategies in traffic management for such a dynamic, fast-growing city result in huge economic losses, environmental damages, and perils to public safety [15]. Machine learning integrated with ITS encompasses great opportunities but also raises some not trivial challenges:

Detection and Prediction: Keystones in effective traffic management are the accurate detection and prediction of the traffic conditions. These systems already built inadequately perform under conditions that are changeable operationally, such as the various scenarios of weather, different lighting conditions, and erratic traffic behavior owing to roadwork or traffic accidents [16]. Hence, models which can assure high levels of accuracy and reliability at real time under all these conditions are in critical need and are the hardest to support.

Real-time Processing Capabilities: There is a lot of data that ITS has to deal with in real time from many sources, including cameras, sensors, and GPS devices. Of course, huge amounts of data have to be analyzed quickly so that traffic management decisions can be made in an instant [17]. Even the most contemporary systems do not have computational efficiencies such that silky processing occurs without any delay at these scales of data, making most traffic control measures suboptimal, which could further increase congestion and accidents.

Integration to Complex System: The integration of advanced ML models in existing ITS infrastructures triggers enormous integration challenges. Mainly, it is concerned with compatibility with the existing hardware and software, system stability, and the scalability of the ML solution over other urban settings. Every urban area normally experiences relatively different traffic patterns and involves different infrastructural constraints arising; hence, the need for customizable but scalable ML driven solutions.

Proactive Safety Measures: Conventional ITS systems are mostly responsive to the conditions at that time and do not predict. There is a need for proactive systems capable of predicting and preventing potential hazards prior to incidents more than ever before [18]. A huge challenge is the development of predictive models that can interpret real-time data effectively and predict dangerous conditions recommending real-time preventive measures.

This is apart from being an answer to dynamic adaptability and continuous learning, where the change occurrences within urban traffic are not static but dynamically changing with urban development, changes in population density, and shifts in transportation policies [19]. Such ITS systems, therefore, should be adaptive to these events of change while continuously learning from new data to improve predictive accuracies. This will require that ML algorithms be designed in a very adaptive way such that they update themselves as and when new data comes in without frequent reprogramming or human intervention.

Data Privacy and Security: ML in ITS covers the collection, processing, and subsequent storage of significant data, which some may be confidential [20]. This warrants assurance that privacy and data security are held and, therefore, not breached. Further, systems should also serve as imperviousness against data manipulation and cyber-attacks in order to avoid a risk to safety that could ensue from traffic management decisions.

In other words, the above challenges describe the apparent complexity in integrating ML into ITS, which further suggests that there will be sophisticated solving proposals. For this purpose, these challenges shall be critically scrutinized so that new ML techniques that can be brought up that increase functionality and efficiency of ITS, hence improving traffic flow and safety in urban areas.

1.4 Thesis Objectives

The dissertation delves into the rigorous implementation of Machine Learning Technologies in an Intelligent Transportation System, in the pursuit of effective urban traffic management and road safety. The research will be carried out to spell out complexities related to modern traffic systems and challenges that are related to a number of distinct but interconnected objectives:

1. Develop and Validate Advanced ML Models for Traffic Monitoring:
   Develop deep machine learning strategies for identifying and predicting traffic metrics such as flow, congestion, and pedestrians moving about with high fidelity in a variety of urban conditions [21]. Develop ways to ensure resiliency of those models against environmental variabilities that could give consistent performance regardless of discrepancies in both weather and lighting [24].
2. Enhance Efficiency of Real-Time Traffic Data Analysis:
   Research, develop, and optimize computational methods for real-time handling of huge datasets emanating from the various traffic sensors and cameras to allow a quick response in traffic management [22]. Exhibit the capability of such methods to facilitate effective dynamic control of traffic—hence resulting in the elimination of congestion bottlenecks and smooth movements.
3. Seamless Integration of ML Algorithms with Existing ITS Frameworks:
   Make a modular integration strategy that will allow new ML designs to be put into the operational traffic management systems without ruining their operational integrity. Tailor this strategy in such a way that it promotes flexible application across urban layouts and varying styles, so that it can be applicable in many city infrastructures.
4. Pioneer Proactive Traffic Safety Mechanisms:
   Develop predictive models in forecasting the potential for a traffic accident before it ever occurs. Make use of such pre-emptive prediction models that would estimate the effects the models could have in reducing incidents related to traffic and increasing safety for urban users on roadways.
5. Implement Adaptive ML Systems for Evolving Urban Traffic:
   Develop ML systems capable of autonomously adapting to changes in traffic patterns and urban growth through self-learning relative to data inputs to the

system [23]. These must be proved to be continuously workable and improvable for predictive accuracy as algorithms update their learning.

6. Guarantee Data Security and Privacy in Traffic Management Operations: Developing stringent data handling procedures within ML-based ITS for assuring user privacy and data integrity. Develop in-built defense mechanisms within the system to defend against cyber incursion and assure that traffic management operations can be trusted.
7. Evaluate Socioeconomic Benefits of Enhanced ITS:
   Analytically review the minimization in the typical urban traffic problems of congestion and pollution that are brought on by ML-enhanced ITS and test the direct environmental and economic advantages [25]. Analyze quantitatively the reduction in costs incurred from traffic management and improvements in energy efficiency derived from these advanced systems.
8. Formulate Policy Guidelines Based on Empirical Findings:
   Synthesize research outcomes into actionable policy recommendations that may help urban planners and decision-makers in adopting and scaling up machine learning-based intelligent transport systems. Identify how possible future research would be able to further calibrate the integration of machine learning in traffic management and through that enhance the benefits worldwide.

These objectives are well aligned to address how the application of machine learning techniques directly can be used to improve the functionality and reliability of traffic management systems, thus making urban environments safe and efficient.

1.5 Working

This work will now discuss the integration of machine learning with advanced features of models to effect improvements using ITS in traffic flow and safety. The present paper makes use of many model capabilities in recognizing patterns and predictive analytics, including Support Vector Regression, long-short-term memory (LSTM), among others. It starts by collecting big data from varied sources, including traffic cameras and sensors, satellite images, and real-time and historical traffic data [26]. Thereafter, the data is cleaned before being fed into the model.

After the data preparatory process, this is followed by enforcement of machine learning algorithms. These models are trained for detecting patterns and prediction of potential traffic disturbances within them, which is validated against subsets of the prepared data for improvement in accuracy and reliability. Real-life applicability of these models is tested in controlled environments or pilot programs before it enables assessment and modification by important performance indicators such as F1 scores, accuracy, sensitivity, and specificity.

Finally, the validated models are integrated into the existing ITS infrastructures in order to empower them to make better, more real-time decisions. The developed models in this study will be integrated for adaptive traffic light control and dynamic routing functions so as to promptly respond to accidents [27]. This, therefore, proves that machine learning can bring a lot of changes to improve the quality of ITS by making traffic management systems really adaptive and efficient in dealing with all types of traffic congestions. In line with the overall aims of creating smarter and safer urban transport systems, such intelligent systems can help to predict traffic conditions and respond dynamically in a manner that serves to decrease congestion and improve road safety.

1.6 Thesis Outline

- The Introduction of the thesis sets the scene by summarising the implementation of artificial intelligence in Intelligent Transportation Systems (ITS). It explores the motivation behind adopting advanced machine learning techniques to tackle issues related to traffic flow and safety. The introduction further discusses the operational integration of these technologies within ITS, the specific traffic-related problems they aim to solve, and outlines the objectives of the thesis. This section prepares the reader for a deeper exploration of the topic by establishing the framework and relevance of the research.
- Following the introduction, the Literature Review section delves into previous research in the field, examining past work on ITS and the role of machine learning. This review highlights key studies, identifies gaps in the existing methodologies, and justifies the research approach taken in this thesis, linking past insights with the current research focus.
- The Methodology section describes the datasets utilized for training and validating the models, the software and libraries employed, and the specific machine learning techniques and models developed for this thesis. This part is crucial as it details the experimental setup and the scientific methods used to investigate the research questions.
- The machine learning models to be used for the research are to be discussed thoroughly in the Model Discussion part of the thesis. The underpinning theories and configuration have been much discussed for a clear understanding of the rationale of selecting every model and how they contribute to solving the identified traffic problems.
- Results and Discussion: This section elaborates on the presented and analyzed outcomes produced by a machine learning model. It gives detailed metrics, such as accuracy, precision, recall, or other relevance measures, and discusses what the results may infer relative to the effectiveness by which models improved ITS.
- The section Conclusion, Future Work, and Social Impact in this chapter wraps up by applying synthesis of findings, re-mentioning contributions to ITS and machine learning, and laying down roads for future research. An excursus into the more general social consequences of the application of advanced machine learning technologies in ITS systems is made in the concluding section.

This structured approach would ensure a comprehensive presentation of integrating machine learning into ITS, handling the complete journey from conceptualization to practical implications of its operation and, at the same time, would aim at providing invaluable insights in order to enhance traffic systems with state-of-the-art technologies.

CHAPTER 2

LITERATURE REVIEW

This chapter reviews the literature on algorithms applied in machine learning and automated transportation systems. So as to identify with ease what the most important studies and breakthroughs are, it critically reflects on those that have built current practices through references to a range of developed models that use machine learning techniques to make sure that growth exists in safety and flow through traffic. This section serves not only to illustrate the methodologies and findings from seminal works but goes further to discuss how effective such approaches are and their limitations. An analysis of these contributions in the survey shows shortcomings in the present state of the ITS research, especially when it comes to interoperability of the systems and real-time processing capabilities. Specifically, their weak integration and real-time processing set a stage for the thesis to propose novel approaches that strive to bridge these gaps and push boundaries in what machine learning can achieve in this realm of ITS.

Kuok et al. (2021) studied the effectiveness of the integrated WEMDI system by comparing the performance of this system with that of the model of Google Maps and other conventional re-routing systems using the PEMS4 dataset. The experiment result came out to prove that with the WEMDI system over traditional re-routing systems, the traffic management factors have greatly improved, increasing from 38% to 44%. Moreover, with the prevalence of about 50% missing data, a system performance increase of 19.39% was also uncovered, proving the fact that the WEMDI system possibly robust under adverse conditions. This means that the WEMDI technology will become a very valuable resource in the traffic control domain for the simple fact of its high impact beyond current methodologies in efficiently handling incomplete data sets for the optimization of the flow of traffic [28].

Cong and Pei et al. (2021) have also shown that SVM methods are far better for traffic forecasting than SVR. The former brought the error rates down to 0.7898 and a mean-squared error of 0.6519 with PEMS8, while the previous approach does much less. These results suggest that SVMs are more accurate and effective, so it is a useful method for traffic management systems [29].

Chen et al. (2020) They conducted a study with the YOLOv3 model on the UCAS-Avenue dataset and found it to be working well in predicting the flow of traffic. In their results, it worked beautifully as it takes information from edge gadgets at around

37.9 pictures per second while maintaining a level of accuracy of 92%. The results indicate that YOLOv3 can give a combination of both points—at one-point, low latency and high precision—in real time traffic analysis, thereby suiting the design type for edge-based real time traffic monitoring systems [30].

Wang et al. (2020) Prediction superiority of the Rear-end Collision Prediction Model in rear-end crashes over other methods, based on outcome-based descriptions, with those based on Berkeley, Honda, and multi-layer perceptron neural network techniques. The RCPM presents potential to enhance crash prediction systems by providing rear-end collisions with more reliable and effective forecasting [31].

Zhou et al. (2020) Finally, the effectiveness of VGRAN was reported over the dataset PEMS4, where besides incorporating deterministic spatiotemporal modeling and reducing the uncertainty of vector node representation, the model inherently provides a boost to the performance of the sensor network-based traffic forecasting system, thus allowing the model to make better predictions for the dynamic time-varying property of sensors and rather complicated topological structures of the sensor networks. Thus, it is easy to infer that the VGRAN model stands a good potential of leading to the development of a system for forecasting traffic into one which is more effective and accurate [32].

Neetesh et al. (2020) analysed the performance of the Dynamic Intelligent Traffic Light Control System with the dataset PEMS4 in terms of its effectiveness and efficiency over fuzzy neural networks and priority-based methods. The outcomes of the research study established that the DITLCS method outperforms classical methods in traffic management and also enhances the efficiency of traffic control systems. This in effect implies that DITLCS can take the performance and design of traffic management systems to levels that are really responsive and effective [33].

Shengnan Guo et al. (2019) focused on the capabilities of an attention-based spatial-temporal graph convolutional network and its two graphs in the datasets PEMS04 and PEMS08. They showed that the proposed ASTGCN can achieve better performance in traffic prediction than state-of-the-arts recently appearing with lots of diverse performance metrics. The general improvement can be attributed to better capturing of spatial and temporal relations in the ASTGCN traffic data due to the improved structure of the convolutional graph network. The outcome indicated that ASTGCN provides a better alternative for traffic forecasting compared with traditional deep learning models and is more precise and credible [34].

Li et al. (2019) using an in-depth research method based on the PEMS8 dataset, the performance of various models was established: Artificial Neural Networks, Support Vector Machines, Regression Trees, and K-Nearest Neighbors. Their findings show that these methods improve prediction accuracy when applied to data both from upstream and downstream traffic rather than data only from the segment under consideration. The above stresses the need to construct more holistic traffic forecast systems to acquire more contextual views. The research shows that full traffic-flow context can highly enhance the effectiveness of models for prediction construction, providing ground for highest measures of both accuracy and reliability to be applicable in predictions for the sake of decision-making in traffic management [35].

Ferdowsi et al. (2019) applied a cocktail of deep learning models, such as LSTM, RBM, RNN, and CNN, to improve the architectural framework of the Traffic Information Systems through edge analytics, wherein the focus of their study revolved around the implementation of these advanced models in an appropriate edge computing framework designed for the safe and secure traffic information process, respectively, in relation to their work involving the PEMS8 dataset. The combination from these edge analytics with those deep-learning techniques substantially improved the safety and trustworthiness of the TIS. That is to say, such combinations are shown to speed up the data processing, focusing not only on overall system performance but also on its safety. This appears to be an extremely encouraging way of developing traffic management systems in terms of practical realization, emphasizing that the local computing carried out by deep learning is supposed to serve for better performance and greater security [36].

A. Ashwini et al. (2023) used Binarization Search Algorithm to check its utility on images, mainly camera pictures. It was measured through a Peak Signal-to-Noise Ratio, in which the algorithm produced a good score for its quality at 24.04 PSNR. Such a result shows the ability of the algorithm to improve image quality inside applications where clear image binarization is necessary. The increase in PSNR indicates a significant improvement in the clarity and quality of images, therefore suggesting that this algorithm might be really useful for environments that require very precise analysis and processing of images [37].

Ravilla Subramanyam Prashanth et al. (2023) also applied the use of Convolutional Neural Networks (CNNs) while conducting research regarding the analysis of images from a Kaggle dataset, and in the subsequent testing, they realized a great accuracy of 96.5%. This demonstrates the powerfully capable application of CNN for handling complex tasks of image recognition, tested over and over again for its effectiveness in meaningful pattern and feature extraction from vast data. This level of extraordinary accuracy suggests that CNNs constitute very promising tools for most applications requiring precise image recognition, from medical diagnostics to Intelligent Transportation automated systems [38].

Chen et al. (2021) used YOLOv5 to analyze excellent object detection performance on the GTSRB, VeRi-776, and TuSimple datasets, with mAP at an IoU threshold of 0.5 for all classes, equaling 97.70%. This high mAP score combined with evaluations on metrics like the F1 score will establish that YOLOv5 is effectively accurate for the detection, localization, and classification of a wide array of objects across different datasets. Further, the results highlight the robustness that this model exhibits through various real-world scenarios, thus making it very powerful for application wherein high precisions in object detections are required, i.e., within autonomous driving and traffic management systems [39].

Zhao et al. (2020) in the year 2020, Measuring 99.2% accuracy stated through the application of Convolutional Neural Networks for their findings, relating to the German Traffic Sign Recognition Benchmark. This, therefore, proves CNN to be very useful in accurately detecting and classifying the various traffic signs, which greatly help in developing ADAS and autonomous vehicle systems. This high accuracy validated the potential of CNNs to deal with complex visual tasks and pointed to their use in promoting road safety by recognizing traffic signs [40].

Chen et al. (2019) In fact, the YOLOv3 model, the GTSRB, and TuSimple developed datasets for running average precision, leading to measurements of 96.10%. Indeed, a threshold is adopted, with mAP over 96.10% at an IoU of 0.5 for all the classes. This level of performance clearly demonstrates how powerful YOLOv3 is in carrying out object detection and classification tasks in CCTV streams, particularly those required to have very high precisions across applications in recognition of various visual features. The model is under analysis with the F1-score governed by the most optimal capability of YOLOv3 in handling the trade-off between precision and recall under predictions. These results support again the idea that YOLOv3 needs to be applied in practice, especially when ensuring very high accuracy and reliability in object detection for tasks such as autonomous driving systems or traffic monitoring applications [41].

Ghesu et al. (2018) in implementations over the German Traffic Sign Recognition Benchmark with a 95.8% accuracy rate for the model used. It confirms that, indeed, YOLOv2 can have the ability to recognize and categorize the traffic signs with enough accuracy, which is a very important function for autonomous vehicle systems or ADAS. With the high accuracy rates, YOLOv2 is going to empower itself as the powerful real-time detector for traffic signs in order to make automation in driving more secure, with a lot of traffic management [42].

Belaroussi et al. (2018) achieved object recognition for traffic signs through the application of R-CNN on the German Traffic Sign Recognition Benchmark. In fact, their findings with respect to this direction under consideration referred to an accuracy rate of 97.2%, speaking for itself with respect to the value of R-CNN in general and this domain (that is, image object detection). Such a model is expected to make a major gain quite well in precise classification and detection of traffic signs, which are key for any means of developing very responsive visual perception systems for self-driving and traffic surveillance: highly reliable even under hard environmental conditions. The new successes of R-CNN also suggest that it has broader potential to be used in the enhancement of responsiveness and accuracy in operation of automated systems in real-world environments [43].

Gao et al. (2018) reported the precision rate that amounts to an accuracy of 97.6%. This research demonstrates how the Faster R-CNN can be successfully used for real-time, accurate detection and classification of traffic signs in order to support modern automotive technologies serving either a fully autonomous vehicle or ADAS systems. In this respect, the high accuracy rate achieved by Faster R-CNN in this study may help very strongly underline its suitability for tasks demanding real-time precision in object recognition and, most importantly, turning this algorithm into a viable tool for robust solutions in traffic and vehicle automation [44].

Bai et al. (2017) had earlier researched the capability of Deep Multi-Task Learning into the analysis of GTSRB, from which accuracy was realized at 97.5%. This approach uses neural networks, which are capable of handling several learning tasks at the same time, thus enhancing the model generalization effectively from task to task. In the research, high accuracy was obtained, indicating how the attainment by multi-task learning frameworks may perform on efficient recognition of complex information, specifically detection and classification of traffic signs. Such enforcement considerably helps in model robustness during the learning process and guarantees the optimization of computational resources. Therefore, the best solution to advanced traffic management systems that will be implementing autonomous driving is provided [45].

Yousef Magdy Elbon et al. (2022) applied YOLO V4 to detect traffic lights in the LISA Traffic Light dataset and were able to achieve an accuracy rate of 92.29%. The work reported good performance by YOLO V4 for real scenarios in which detection of traffic signals is important within the accurate and timely functioning of automatic driving systems and intelligent transport systems. The high accuracy rate proves the robustness of YOLO V4 under bright light, even with foul weather conditions, which will certainly be a decent choice for enhancement in traffic management and road safety improvement based on advanced machine learning technology [46].

Zakaria Ennahhal et al. (2019) applied the very latest technique for object detection—R-FCN, Faster R-CNN, and SSD—over the LISA Traffic Light and Bosch Small Traffic Light datasets. A case in point is the work by Zakaria Ennahhal et al. (2019) where they have reported that Faster R-CNN performs a mAP of 76.37% on the LISA dataset. This shows the performance of such much faster R-CNNs could be in detecting traffic lights, giving an impression that it can handle difficult situations effectively that could arise commonly in the urban traffic setting. It is evident that this also further proves the applicability of Faster R-CNN in critical applications within intelligent transport systems that require the precise detection of traffic lights, stoplights, or traffic signs to support automatic vehicle guidance and for managing traffic [47].

Morten B. Jensen et al. (2017) tested multiple V1, V2, and V3 YOLO models on LISA Traffic Light and LARA Traffic Light test datasets. The most state-of-the-art tested—that is, YOLO V3—has thrown a really good AUC of 90.49%. This proves that YOLO V3 can achieve better detection for traffic lights, a core function for automation and safety of intelligent transportation systems. Conclusion: Conclusively, since it was recorded within the fairly high AUC values of the range 89-94%, the results would indicate that YOLOv3 is strong in the separation between finding a traffic light and locating no traffic light under all kinds of challenging conditions in real-world traffic and control driving applications [48].

Chenxi Lyu et al. (2023) discussed the capabilities of EfficientNet B0 and EfficientDet to make object detection, with a focus on the ability to test these models on the LISA Traffic Light and German Traffic Sign Recognition Benchmark (GTSRB). His study proves that this efficiency- and high-accuracy-oriented EfficientDet brought up to 77.54% mAP. This is indeed a good indication that it was pretty successful in the task of recognizing and classifying the traffic signal and sign, which will be crucial for intelligent traffic systems. Most likely, it would have proceeded to evaluate other measures like the F1 score and Log Average Miss Rate to give a complete account of the detection reliability and precision of the model, thereby the capability of EfficientDet in the improvement of real-time traffic monitoring and control systems [49].

Emin Güney et al. (2022) conducted an experiment on the GTSRB dataset using YOLO V5 and reported an accuracy of 75%. The current project tests applicability for traffic sign detection, which is a basic prerequisite for the implementation of technologies in autonomous driving and traffic management systems. Besides this basic evaluation, possibly, the research will underpin other key performance measures set up, such as precision, recall, and mAP. More so, such metrics further help delineate the model's capacity for correct classification of traffic signs, minimization of false positives, and correct prediction of a wide range of sign types; hence, presenting a nuanced perspective regarding YOLO V5 usability in real-world applications where reliable and precise traffic sign recognition is crucial [50].

Zhenchao Ouyang et al. (2019) have found in their study that the lightweight versions of the YOLO model, like YOLO3-tiny, hit 32.47% recalls when they compared their performance to various models working on object detection, such as Faster R-CNN and SSD, with YOLO3, whose datasets came from WPI, LARA, Bosch, and LISA Traffic Light. It mirrors a model's capability to pinpoint relevant objects, for example, traffic lights, in different environmental settings by the way in which datasets represent these environments. The work also factored in the use of Intersection Over Union, which was able to give an even clearer indication of how well the bounding boxes predicted are made by the models. However, the relatively low recall rate of YOLOv3-tiny suggests that it is challenging to capture all the relevant instances—an important factor for the traffic light detection system to work reliably in ITS applications [51].

Shujia Yan et al. (2021) by employing K-Means clustering; their research focused on the Berkeley DeepDrive Traffic Light dataset. This hybrid method allowed the processing of the more subtle signal detection process, where K-Means helped in parting and clustering the traffic light instance before processing the same by YOLO V5. Such a novelty in methodology ensured an increased mean average precision of 63.3%. This metric is averaged mAP, that is, it estimates in parallel the performance of the model for traffic light detection in difficult urban driving scenarios. Object detection tasks in such traffic environments with high population densities may, therefore, offer very high potential to combine YOLO V5 and K-Means techniques in developing safer and more efficient traffic management systems [52].

Xi Li et al. (2018) Some works make use of both the VIVA and LARA datasets to test the performance with detection frameworks like SLD (structured learning detector) and ACF (aggregate channel features) of Faster R-CNN. The tests showed quite positive effects of detecting traffic lights on both LARA sets, achieving an Area Under the Curve (AUC) of 71.50% in the VIVA dataset and 91.97% in the LARA dataset. It is shown that the Faster R-CNN method is effective in complex visual environments and is able to perform accurate detection of traffic lights. The strict AP and AUC scores, especially on the LARA dataset, prove an excellent possibility for joint methodologies like this one in improving the accuracy and reliability of automatic traffic light detection systems, which are essential for intelligent transportation systems [53].

Yi Yan et al. (2023) developed an improved authors' method, introducing the integration of the SSD framework with robust backbones as: ResNet50 and VGG16 to analyze the China Traffic Sign Data. They obtained their setting with results of 91.23% in Average Precision and 93.26% in Average Recall. These are metrics used to showcase the high system relevance in detection or recognition of traffic signs for a model: mAP and mAR, respectively. The enhancement of backboning SSD with ResNet50 and VGG16 increases the capacity for more complex and deeper feature extraction from the image; hence, performance really gets uplifted on how objects are detected. The results of this study point to the high effectiveness of this enhanced model of SSD in service to intelligent transportation systems in which precise traffic sign recognition is very useful for navigation and safety [54].

Peilin Liu (2023) focused on advanced traffic light detection using YOLO V5 upgraded with RepConv on both Bosch Traffic Light and S2LTD datasets. The experiment showed that the technique in upgrading YOLO V5 by RepConv had a few advanced capacities of detection, on average mAP of 73.5%, and in the S2LTD dataset reached 94.3%. From these results, it can be concluded that integrating RepConv with YOLO V5 truly improves the treatment of models toward accurate detection of traffic lights across many different scenarios. Specifically, the high mAP scores achieved in all recognition tasks for the S2LTD dataset emphasize the potential that will be experienced using this approach to develop a reliable detection system for deployment in cities to manage and organize better traffic and urban life [55].

Zarei et al. (2023) considered the approaches for using a Conditional Generative Adversarial Network in modeling frequency data in accidents, within a non-parametric empirical Bayes method. They conducted estimation of the new method in real accident records and simulated data to give a thorough test of applicability. The performances of the new CGAN-EB model were compared to the traditional NB-EB, respectively, for model fitting, predictive performance, and network screening effectiveness. All results show that CGAN-EB outperforms the traditional NB-EB for parameter estimations of accident frequency models. This development suggests a potential way of bigger impacts of CGAN-EB on traffic safety analyses since high-risk areas are detected for the proper taking measures to mitigate those [56].

Amorim et al. (2023) developed a machine learning-based algorithm to analyze factors regarding traffic accidents on Brazilian federal highways. This project comprises a high number of variables, geographical data, meteorological conditions, and means of road accidents; accordingly, it falls under supervised learning algorithms. Good results for the neural network model compared with the other tested algorithms: 83% accuracy, 83% F1, 84% precision, and 84% recall. This indicates that the neural network will most likely be highly predictive in decisions and analyses of the dynamics of car accidents, and that this probably will be the basis for improving road safety efforts on federal highways [57].

Saravanarajan et al. (2023) discussed and proposed a new algorithm for vehicle collision detection with the help of a regional-based detector, CNN8L, regional proposal network, and feature extractor VGG 16 through transfer learning. The CNN8L is a small-sized, convolution neural network serially arranged to make proper identifications of correspondingly interesting regions of vehicular environments. The experimental results presented here confirmed the superiority and excellence of the developed VGG16-CNN8L combined model over the others, with an ADR robustly at 86.25%, maintaining a fair FAR of 33.00%. This further attests to the potential of such a holistic approach to enhancing accuracy and reliability in systems for collision detection and providing a marked tool for ensuring improvement in road safety [58].

Gutierrez-Osorio C. et al. (2022) developed a hybrid deep learning model for predicting traffic accidents. The model combined Convolutional Neural Networks and Gated Recurrent Units in its structure. Novelty in this model relies on the data collection approach, regarding traditional open data sources and data from social media. This way, a greater incidence of reports on situations that under 'normal' circumstances does not get caught in official statistics can be captured. The model involves careful feature engineering and data quality assessment into the process of embedding, which greatly enriches the whole information collected. The performance of this hybrid DL model is rigorously compared with baseline algorithms and taken together with outcomes documented by previous researchers in this field. Some of these results presented give hope that the ensemble model will outperform not only conventional baseline algorithms but also other deep learning models discussed in the literature. As a result, the model's performance superiority implies its potential application in supporting preventive planning by traffic control groups—most importantly in the highly accident-prone spots—such as busy intersections. Such capability points towards a significant enhancement using machine learning for making life better in terms of public safety and traffic management [59].

Comi et al. (2022) proposed a methodological approach that employs data mining techniques in the context of traffic accident data within the Rome Municipality. More specifically, they targeted the application of both descriptive and clustering analyses to find important patterns and causative factors related to road accident occurrence. An important part of the study dealt with the influence of different vehicle types and road infrastructure conditions on the resulting severity of the accident. In this study, it was found that data mining has very high potential not only in identifying accident-prone areas but also in formulating some targeted strategies so as to reduce the rate of accidents. The findings from the study by Comi et al. suggested that, in fact, data mining enhances put in place measures concerning traffic safety and gives very actionable advice during the process of urban planning and traffic management [60].

Zheng et al. (2020) researched the short-term behavior in traffic flows using a sophisticated deep learning model for intelligent transportation systems. A model of this nature combined bidirectional long short-term memory for the representation of daily and weekly traffic patterns and an attention-based long short-term memory unit for the encoding of spatial and short-term temporal information. They further integrated the two modules and developed it into a complete system that had the capability of improving traffic forecasts. The new proposed methodology showed significant potential to increase the improvement of urban mobility and advance intelligent transportation systems by offering more accurate predictions and better-informed traffic management strategies [61].

Chen et al. (2021) utilized the Apriori method to uncover associations between various variables contributing to traffic crashes. They further used several machines learning algorithms like eXtreme Gradient Boosting (XGBoost), Classification and Regression Trees (CART), and Support Vector Machines (SVM) in the classification of crash severity. The Shapley Additive Explanations (SHAP) were further used to determine the relative importance of every variable. It is to be noted that 75% recall is achieved at the highest level of the recall rate with XGBoost, whereas G-mean is at 678.29%. Integrating Apriori and XGBoost into the analysis of a study concerning the crash severity brought forth all known characteristics and interactions, so this is invaluable information for traffic safety improvement [62].

Choi et al. (2021) came up with a system for car crash detection using the combination of Gated Recurrent Units with Convolutional Neural Networks. The inputs for this system are the data from the dashboard camera in the form of audio and video, which are classified using multiple classifiers. In checking system efficiency, individual classifiers were tested with either audio or video data. The results indicated that the combined GRU-CNN model outperformed a single classifier run on YouTube footage of head-on car crashes, indicating that it will apply complementary strengths to audio and video data for improved accuracy and reliability in car crash detection systems [63].

Rahman et al. (2019) accident prediction models on a macro level. In our study, we are focusing on the prediction of accidents in bicycle and pedestrian categories. The authors used various machine learning approaches, and gradient boosting emerged as one of the most optimal ensemble techniques that showed up over the experiments. In general, all strategies exceeding the Decision Tree Regression model will be better, but Gradient Boosting turned out to be more accurate and predictive. This indicates that ensemble methods, especially gradient boosting, are highly advantageous for the prediction of macro-level crashes and would provide well-informed safety measures and urban planning [64].

CHAPTER 3

METHODOLOGY

Thus, developing artificial intelligence application in the ITS framework can bring the correct management of traffic loads and safety. It is, therefore, effective in presenting data acquisition procedures and preparation in the chapter relating to datasets sourced from national traffic databases to local traffic management systems. It shall, therefore, emphasize upon the need for effective data quality and consistency for realizing applications of ML effectively. It will then present the selection and use of appropriate ML algorithms that will be used to help in solving some specific identified constraints with the existing ITS, such as sign recognition and prediction of accidents, accompanied by a justification of each of the proposed solutions with respect to factors like computational cost and prediction accuracy, among others [65]. Then, this thesis will try to explain the strategy for where the models need training through discussion about different methodologies employed in experimentation, such as cross-validation, which is applied during parameter optimization and overfitting avoidance. For this, different data clusters and virtual reality sets would be applied on the models during development so constant testing and validation, strictly, ensures its effectiveness and reliability in practice. Therefore, performance will be tested against specified metrics—such as specificity, accuracy, sensitivity, F1-score, and reactivity—in real time, thereby testing the functionality and effect of each model in the traffic systems. This section will conclude with the iterative refinement of the models through active usage of feedback from initial deployments to make them better adaptive and useful for changing urban traffic conditions. Hence, it sets the methodological ground for achieving the goals set forth in this thesis for advanced ML solutions toward making ITS better.

3.1 Datasets

3.1.1 PeMSD4 Dataset

1. Source and Scope: The PeMSD4 dataset is part of the California Department of Transportation's broader Caltrans Performance Measurement System. It is specifically called District 4, and it covers mainly the freeway system around the San Francisco Bay Area.
2. Data Composition: The data for this study consist of high-resolution traffic data collected through over 700 sensors embedded in the freeway network. The

sensors collect traffic metrics, including vehicle counts, occupancy, and speeds in 5-minute intervals.

3. Data Characteristics: One main feature of the PeMSD4 dataset is that it fully captures varying traffic scenarios such as peak hours, the midday lull, and late-night times during weekdays and weekends. This dataset offers an enriched source of real-time traffic data that paints a vivid image regarding dynamics associated with urban traffic in one of the most congested regions in the United States.
4. Use in Research: This dataset is one of the several key datasets supporting the development of models for traffic prediction within the ITS field. Such temporal and spatial data is used by machine learning models to predict traffic flow patterns, pinpoint potential bottlenecks, and suggest optimal strategies for traffic management. The granularity of the data allows for fine-grained analysis and modeling of traffic behaviors under various conditions.

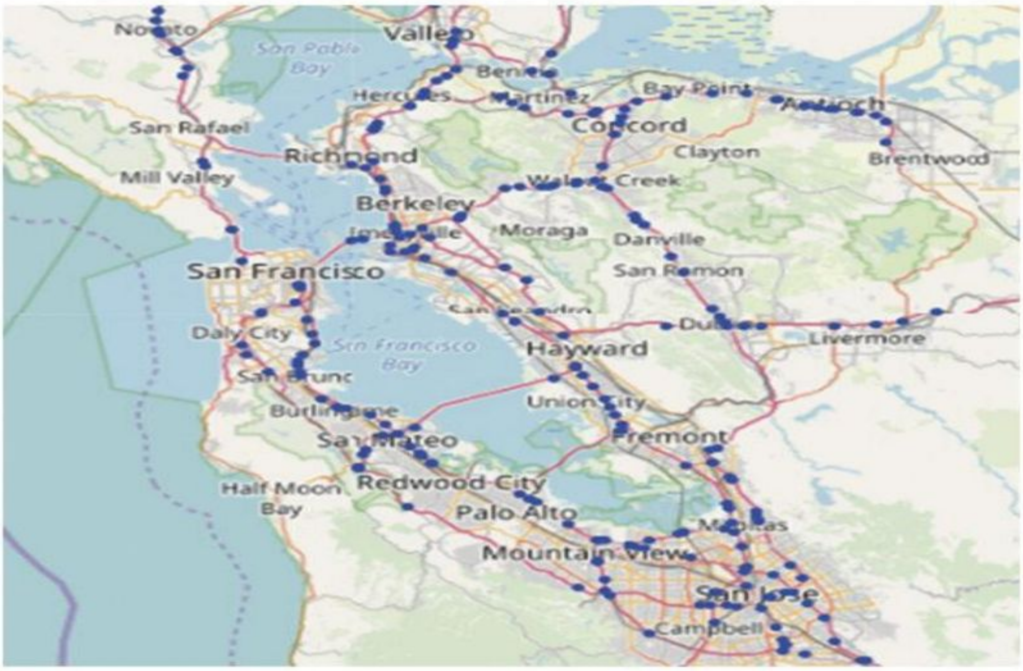


Fig. 3.1 Sample of PeMSD4 dataset [66]

3.1.2 PeMSD8 Dataset

1. Source and Scope: Like PeMSD4, the dataset of PeMSD8 is sourced from Caltrans PeMS but applies to District 8 of California, which includes parts of Southern California, more precisely, that of Riverside and San Bernardino counties.

2. Data Composition: Aggregates data from about 500 sensors planted along freeways and major highways across the district. Like PeMSD4, the information collected by these sensors is in traffic volume, speed, and lane occupancy, and that at a five-minute interval.

3. Data Attributes: The PeMSD8 data set is extremely useful in the study of traffic trends in a region characterized by important suburban to urban commuting trends. The variability of the traffic flow, caused both by seasonal population fluctuations and major public events, will result in rather typical weekday-versus-weekend anomalies and lend this setting dynamism for traffic analyses.

4. Usage in Research: For applications using ITS, PeMSD8 provides a dataset with unique traffic dynamics, mentioned due to the urban center but also large suburban areas. It is used in machine learning-based models to enhance predictive accuracies in traffic density forecasts, speed prediction, and solutions to manage congestion. Researchers leverage this dataset to test algorithms under diverse geographical and demographic influences, enhancing the robustness and adaptability of traffic management systems.

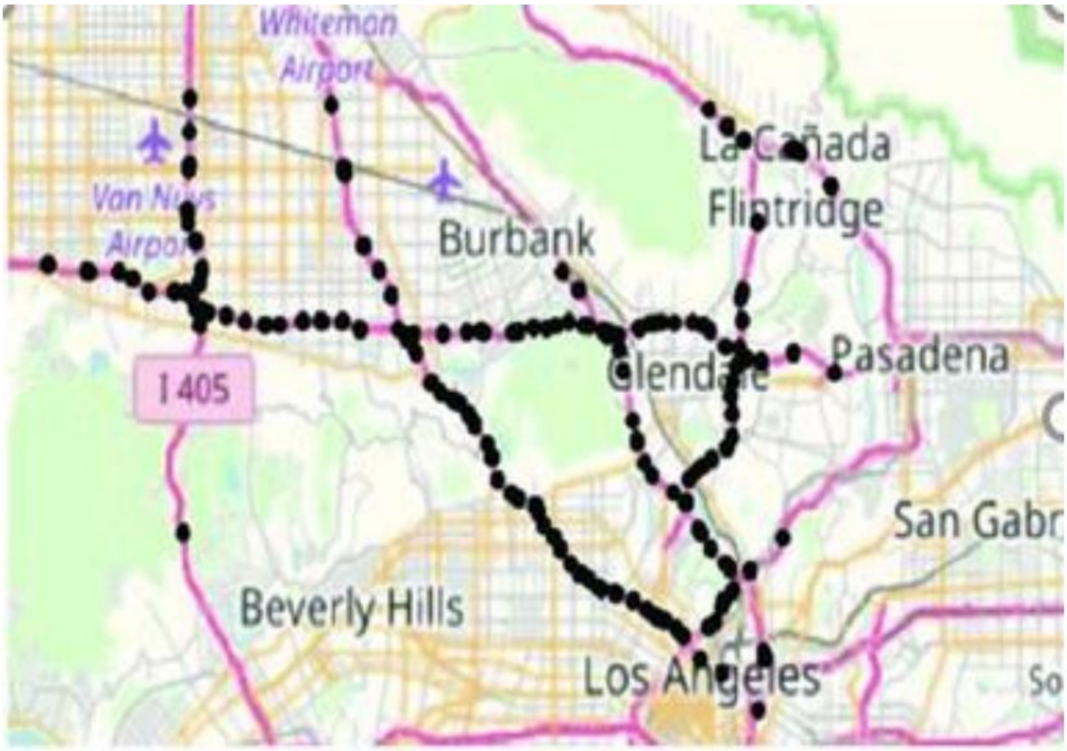


Fig. 3.2 Sample of PeMSD8 dataset [67]

3.1.3 German Traffic Sign Recognition Benchmark (GTSRB)

1. Source and Scope: The GTSRB is one of the well-established datasets created for the competition under IJCNN in 2011, and it is widely used in the research for the recognition of signs which control traffic across the globe.

2. Data Composition: There are 50,000 images in the dataset and are labeled into 43 classes representing different traffic signs. The classes enclose speed limits, warning on hazard, prohibition, etc. Most of the images are subject to large lighting, blurriness, and the physical state of the traffic sign.

3. Data Characteristics: Images in GTSRB were collected in variable illuminations and under different weather conditions, providing strong data that could easily challenge algorithms toward generalization. Each image has annotations of the sign type, making it useful for classification and detection purposes.

4. Usage in Research: You use GTSRB in your thesis to train deep learning models for recognizing and classifying road traffic signs with high accuracy. The dataset variation challenges the deep-learning model for adaptation to real-world variations and environmental conditions.

Fig. 3.3 Sample of GTSRB dataset [68]

3.1.4 Indian Traffic Sign Dataset (ITSD)

1. Source and Scope: The source from which ITSD has been derived is scoped specifically for the traffic that exists in India, capturing the unique signage and the diverse traffic scenarios encountered in the region.

2. Data Composition: This dataset is composed of several thousand images corresponding to an extensive range of Indian traffic signs. The signs in ITSD are labeled with labels corresponding to rules and symbols used in India, often very different from those in Western datasets.

3. Data Characteristics: ITSD contains the traffic signs recorded under varied lighting conditions and different viewing angles, encapsulating realistic scenarios with different problems that occur during the traffic sign recognition by the automatic systems in India.

4. Research Usage: The localized content of ITSD is of paramount importance for developing in India, traffic sign recognition systems, to ensure that models trained are effectively attuned to local nuances and practical applications.

Fig. 3.4 sample of ITSD dataset [69]

3.1.5 Belgian Traffic Sign Dataset (BTSD)

1. Source and Scope: The BTSD contains traffic sign images collected from the roads of Belgium, providing another regional perspective on traffic sign recognition.

2. Data Composition: The dataset includes over 12,000 images, categorized into comprehensive classes that reflect the complete spectrum of Belgian traffic signs. The dataset is noted for its high-resolution images, which are beneficial for detailed feature extraction in ML models.

3. Data Characteristics: Similar to other datasets, the BTSD includes variations in background, sign occlusions, and signs at different stages of wear and tear, presenting realistic challenges for recognition systems.

4. Used in research: Owing to the high resolution of BTSD, more complex models can be trained and developed, which can recognize and classify small or partially obliterated sign boards thereby increasing its accuracy and reliability.

Fig. 3.5 BTSD dataset sample [70]

3.1.6 Swedish Traffic Sign Dataset (STSD)

1. Source and Scope: The collection, which includes unique-to-the-region traffic signs that represent road rules and conditions for Sweden, contains images of traffic sign databases.

2. Data Composition: The database has a large collection of different classes of traffic signs installed in Sweden, which are categorized according to the traffic sign regulations in Sweden.

3. Data Characteristics: For the noted influence of seasonal variations, the STSD is very good; that is, the images are recorded in different seasons, showing against the background of snow, rain, and fog, which is very frequent in Sweden.

4. Usage in Research: The seasonal diversity in STSD is crucial for developing algorithms that perform reliably under adverse weather conditions, a common scenario in Nordic countries. This dataset aids in enhancing the robustness of traffic sign recognition systems under varied environmental impacts.

Fig. 3.6 sample of STSD dataset [71]

3.1.7 LISA Traffic light Dataset

1. Development: The LISA Traffic Light Dataset is developed by the Laboratory for Intelligent and Safe Automobiles (LISA) at the University of California, San Diego, for the purpose of developing traffic light detection systems within ITS and further training and benchmarking of the system.

2. Contents: It has some hours of video footage in which more than 7,000 annotated frames with traffic lights were captured. Each of the frames was annotated with the state of the traffic lights by bounding box coordinates, specifying the position of the traffic lights in the images—red, yellow, and green.

3. Varied Capture Conditions: This applies to recordings in different lighting and weather conditions, as well as the different times of a day and multiple intersections around San Diego. Such variation adds to the authenticity in the dataset, which yields a strong base on which to work while designing traffic light recognition approaches effectively under real-world driving conditions.

4. Traffic Light Variability: The dataset contains traffic lights shown in all imaginable configurations, including single, stacked, shapes, or views that would probably be partially obstructed. These instances provide the algorithms with a better challenge as to how they will find solutions correctly.

5. Applications in research: It is a very crucial tool to provide meaningful training and validation for the machine learning models targeting the recognition and better understanding of the traffic light signals. It also provides a benchmark to compare various traffic light detection models so that one can assess their performances across different urban and suburban backgrounds.

6. Implications for ITS Development: The accurate detection and interpretation of traffic lights are vital for integrating enhanced traffic management systems and autonomous driving technologies. Improvements in these areas contribute to more efficient traffic flow, reduced congestion, and increased safety on roads.

Fig. 3.7 sample of LISA traffic light dataset [72]

3.1.8 Ministry of National Highway and Authority Accident Data Dataset

1. Origin and Authority: This dataset is collected and maintained by the Ministry of National Highway and Authority, which oversees and records comprehensive data on road traffic accidents across national highways and other major roads. This ensures a broad and authoritative scope of traffic safety information, making the dataset a critical resource for nationwide analysis.

2. Details and Data Points: Comprising detailed accident reports, the dataset includes variables such as the location (GPS coordinates), timing of accidents, vehicle types involved, weather conditions at the incident time, and descriptions of the road conditions. It also encompasses demographic details of involved parties (while respecting privacy standards), the nature of injuries, fatalities, traffic volume, and road work disruptions at the time of each accident.

3. Research Applications: In the thesis, this dataset underpins the development of machine learning models to predict accident hotspots and evaluate road safety interventions. It allows for the simulation of traffic conditions to understand how different variables contribute to accidents, supporting predictive analyses that can pre-emptively identify and mitigate high-risk conditions.

4. Policy and ITS Development Implications: The insights derived from analyzing this dataset inform strategic decisions by the Ministry regarding road safety enhancements and traffic management. The data aids in crafting policies that target identified problem areas, evaluate the impact of road safety measures, and refine traffic law enforcement strategies to reduce accident rates and enhance overall road safety across national highways.

Year	Total cases reported	No. of persons killed	No. of persons injured
1998	17,117	6578	17,547
1999	12,503	5953	18,000
2000	12,325	6336	20,555
2001	15,621	7845	26,745
2002	16,452	8452	27,102
2003	16,795	8672	28,215
2004	14,279	5351	16, 897
2005	8962	4519	15,779
2006	9114	4944	17,390
2007	9132	4916	20,944
2008	11,341	6661	27,980
2009	11,031	4120	20,975
Jan-June 2010	5,560	3183	14, 349

Fig. 3.8 sample of accident, injured, death dataset by NHAI [73]

3.2 Software Requirements

The principal objectives of the developed requirements are effective implementation and testing of machine learning models, such as to be able to develop models for enhancing traffic flows and traffic safety in general within an Intelligent Transport System. Successful deployment will call for a robust software environment cumulating support for complex data processing, model training and validation, ITS scenario simulation.

- The principal computer language is Python, fully supporting data analysis and machine learning with a vast number of libraries and frameworks. From the perspective of simplicity and flexibility, Python has become the primary choice for most of the developers to deal with a diversity of needs in machine learning projects within the traffic system.

- Jupyter Notebook acts as a main user interface for coding, debugging, complex data visualization, and result presentation. In such an interactive and versatile environment, varying the model parameters interactively allows for further functionalities, such as the probing of different knobs on the model during tuning.

- Use Git version control to manage the development process and further provide the reproducibility of research.

- The simulation of traffic scenarios and testing the impact of machine learning approaches on postulated models for intervention recommendations are conducted in simulation tools such as SUMO (Simulation of Urban Mobility) or VISSIM applied to modeled environments. Such tools will explain how the models would perform in real-world applications of ITSs.

- HPC resources or cloud computing platforms, such as AWS and Google Cloud, which are typically used in the event of intensive data processing and high-computational power models.

3.3 Necessary Libraries

- NumPy and Pandas for the manipulation and analysis of data. Such libraries provide you with tools to work with large sets of data, which are basic in operations with traffic data in these models.

- Scikit-learn: This is a nice way to implement classical machine learning algorithms very easily and efficiently. It is used widely for tasks such as model training, cross-validation, and calculation of various other machine learning metrics.

- For implementing and training more complex neural network architectures, TensorFlow and Keras were used. These libraries support deep learning models that have been used in this thesis: LSTM and CNNs.

- It can also be computed using PyTorch, since it uses dynamic computation graphs and does memory efficiency with regard to the training of models with large datasets, which is quite typical of an application like ITS.

- Matplotlib and Seaborn are used for creating static, interactive, and animated visualizations to analyze the model outputs and traffic data insights effectively.

3.4 Data Preparations

It comprises data cleaning and pre-processing details, which are key steps in applying machine learning to bring out the best in improving traffic flow and safety in an intelligent transportation system. Data quality is critical for the success of the machine learning models; thus, preprocessing steps need to be taken to ensure that the findings being derived through further analysis are valid and reliable.

3.4.1 Data Cleaning

The first step of the preprocessing sequence includes capturing the data with heavy denoising, collected from various sources such as traffic cameras, sensors, and satellite images. This includes:

- Inconsistencies Removal: Elimination of the timestamp mismatching for data collected, sensor malfunctioning, and misalignments in sources from different data.

- Dealing with missing values: The method will involve handling missing values and data gaps using imputation, for instance. The technique used in imputation, that is, mean imputation or interpolation, strongly depends on the nature of the data and the expected effects on the model's performance.

- Outlier Removal: Outliers in data that would skew the results will be filtered out based on statistical methodologies. Especially within traffic data, anomalies are unrelated to the usual pattern of traffic and, therefore, would adversely affect the model-fitting process.

3.4.2 Data Pre-processing

The main half of the work is just data cleaning. Next comes the preparation of cleaned data for feeding into machine learning models. Some key processes are described as follows:

- Feature selection: Identify the significant features that contribute to traffic flow and safety. This can be a data point relevant to vehicle speed, traffic density, time of day, weather conditions, and accident reports.

- Feature engineering—involves deriving new features from the existing data that will help improve the model's performance. Convert timestamps into categorical types that represent features like 'time of day' or 'day of the week,' which would aid in capturing cyclical patterns in traffic flow.

- Normalization and Scaling: It prepares the data features in such a way that the range of these features does not allow the hitherto developed model to get biased toward the majority level or features that have a large value or scale. This is generally done using Min-Max scaling or Z-score normalization techniques.

- Data Transformation: Data transformation is the process through which data are converted into forms that are usable in machine learning. In time-series predictions, this would also mean further processing, such as organizing the data in sequential windows if we use LSTM networks.

- Data augmentation: It is a technique of artificially increasing dataset size, which helps the model in becoming robust through the addition of diversity in the data. In this method, images can be rotated, scaled, or cropped to generate more examples for training models [75].

These preprocessing steps are very important for minimizing potential sources of errors in model training and maximizing the predictive performance of the used machine learning models. This is an assurance that the data fed to the models is clean, relevant, and congruously organized with the analytic objectives of improving traffic flow and safety features in ITS [76]. Such rigorous data management practices set a good foundation for the current thesis in reliable and actionable traffic management insights.

3.5 Proposed Models

In this thesis, the objective is mainly directed towards enhancement in traffic flow and safety of Intelligent Transportation Systems with regard to machine learning abilities. In this regard, four comprehensive but complementary models have been developed and implemented in such a way that they may resolve manifold challenges faced in ITS. This multi-faceted approach ensures in-depth improvement in various components of traffic systems.

The first part basically involves the support for traffic prediction using the described approach, support vector regression. This model makes an attempt to forecast the traffic condition by employing SVR. This hopes to be accurate, as it is very crucial for pre-emptive traffic management and congestion avoidance. The designed methodology of this model was from data acquisition to the optimization of SVR parameters, so that there are precised and reliable forecasts of traffic.

This paper will focus on advanced detection systems following a prediction of traffic. We present an implementation using an ensemble of Yolo-NAS and Mask R-CNN in detecting traffic lights. This model builds on the strong areas of both architectures to improve the accuracy and reliability of state identification, which is relatively important for automated and semiautomated vehicle guidance systems.

The third part involves traffic sign detection with the ensemble of YOLOv8 and Detectron2. This model improves recognition and classification performance related to traffic signs, providing more appropriate navigation support to both driving assistance systems and autonomous vehicles. The combination of such powerful detection systems anticipates staging out the instances of misinterpretation and enhancing operational efficiency related to ITS.

The ensemble model developed in the last sections of this research combines warning prediction of traffic accidents before its occurrence, which means increasing the level of pre-emptive prevention and minimizing the chances of occurrences. FNNs are combined with LSTM networks to predict traffic accidents.

Each model is developed individually and tested with each step clearly outlined from data preparation to model evaluation. In the integration of these models, it is bound to make an all-encompassing improvement in ITS that will ensure an increased level of traffic management and significantly better safety measures. A structured approach, therefore, is not only effective for addressing the immediate challenges currently faced by traffic systems but for building scalable frameworks into future advancement in intelligent transportation technologies.

3.5.1 Traffic prediction using the SVR

Table 3.1 Process for implementation of traffic prediction model

Steps	**Techniques**	**Procedure for Traffic Prediction Using SVR**
Step 1	Data Preprocessing	Handle missing values, apply denoising techniques, and perform data reduction to streamline the dataset.
Step 2	Feature Selection	Identify and select relevant traffic features (e.g., vehicle speed, traffic volume, time of day) for modeling.
Step 3	Data Segregation	Divide the cleaned and processed data into two distinct sets: one for training and another for testing the SVR model.
Step 4	Parameter Setup	Establish a suitable range for the SVR parameters, considering factors like kernel type, C (regularization), and gamma.
Step 5	Model Training	Input the training dataset into the SVR model to learn the traffic patterns and adjust weights accordingly.
Step 6	Performance Evaluation	Assess the SVR model using the training set to fine-tune parameters for optimal accuracy.
Step 7	Parameter Optimization	If the results meet accuracy standards, finalize the parameters. If not, iterate to improve the model configuration.
Step 8	Testing and Validation	Use the testing dataset to predict traffic conditions; compare these predictions against actual data to evaluate the model's effectiveness.

3.5.2 Traffic sign board detection using YOLOv8 and Detectron2 ensemble

Table 3.2 Process for implementation of traffic sign board detection model

Steps	Techniques	Description
Step 1	Data Acquisition	Collect and organize data about traffic from sources. Make sure that the data is broken down into types, such as the number of vehicles and timestamps. Ensure each record of the three types has all required attributes.
Step 2	Software Setup	Install all necessary software dependencies, including the SVR library from scikit-learn. Configure the computing environment to support extensive data processing and SVR model training.
Step 3	Data Preparation	Normalize data ranges in order to make the values fall on the same scale, impute missing values properly, and identify and treat outliers to ensure that the quality of data is not compromised.
Step 4	Feature Engineering	Select features relevant enough for designing traffic patterns, for example, the time of the day, weather conditions, and types of roads. Feature engineering can further introduce new features which add value to the model in making it more predictively powerful, like developing features describing the flow rates of traffic.
Step 5	Model Configuration	Set SVR parameters: type of kernel and regularization parameters. Find the optimal settings by grid search or similar search techniques in which the best trade-off is between bias and variance.
Step 6	Model Training and Validation	Split dataset into training and validation sets. Train the one mentioned earlier set in terms of performance about the SVR model, namely, on the training set, and strictly keep an eye on the validation set so as not to overfit and to ensure generalization.
Step 7	Model Evaluation	Apply the trained SVR model to the validation set to predict traffic conditions. Assess the model's accuracy, precision, recall, and F1-score to evaluate its performance and suitability for deployment.
Step 8	Implementation and Testing	Implement the model in a simulated ITS environment or as part of a pilot project to demonstrate effectiveness in a real situation. Reiterate improvements based on performance feedback.

Step 9	Optimization and Finalization	Iteratively Improve Model: Get in the loop of re-tuning the parameters and retraining it on new data whenever it becomes available. Finalize setup when this model gets fine-tuned to desired criteria on accuracy and efficiency.

3.5.3 Traffic Light Recognition Based on YOLO-NAS and Mask R-CNN

Table 3.3 Process for implementation of traffic light detection model

Steps	**Techniques**	**Description**
Step 1	Data Collection	Collect a diverse set of images containing traffic lights from various sources to ensure comprehensive coverage of different lighting and weather conditions.
Step 2	Data Organization	Group the images together into different folders according to their labelling (red, green, yellow, and off). Each image should have one annotation file corresponding to it describing the position of the traffic light and its phase.
Step 3	Environment Setup	Install and configure all necessary software and libraries, including the YOLO-NAS and Mask R-CNN frameworks. Development environment setup to support deep learning and image processing tasks.
Step 4	Data Preprocessin g	Resize images to meet the input requirements of both models. Standardize the format of annotation files to be compatible with YOLO-NAS and Mask R-CNN. Apply image augmentation techniques such as rotation and scaling to increase dataset robustness.
Step 5	Model Configuratio n	The parameter fine-tuning for both YOLO-NAS and Mask R-CNN should be set to reach optimum levels of detection precision by setting thresholds for detection confidence in the hyperparameters for learning rate and epoch numbers.
Step 6	Individual Model Training	Manually train the YOLO-NAS and Mask R-CNN models on the training dataset for traffic light identification. Train the models separately until they learn well for these respective tasks. A check should be

		maintained over numerous training sessions in reference to the various performance metrics: loss and accuracy.
Step 7	Ensemble Strategy Development	Develop an ensemble strategy stitching through both YOLO-NAS and Mask R-CNN. The average confidence scores of both models are considered or combined together in a more elaborate way to make an algorithm for decision-making that will give the final prediction.
Step 8	Ensemble Model Training	Train the ensemble model with the strategies developed in step G. Validate the above model in a separate validation set to finely tune the ensemble parameter for competitive performance.
Step 9	Model Evaluation	Evaluate the final ensemble model using a test set. Compute key metrics, i.e., precision, recall, and F1-score, for assessing the accuracy and reliability of the traffic light detection system.
Step 10	Optimization and Testing	Carry out additional optimizations depending on the results of testing and adjustment of parameters. Implement the model in an ITS simulation environment to validate its real-world applicability and efficiency.

3.5.4 Traffic accident prediction through FNN and LSTM

Table 3.4 Process for implementation of traffic accident prediction model

Steps	**Techniques**	**Description**
Step 1	Data Acquisition	Gather comprehensive accident data, including variables such as time, location, weather conditions, and traffic volume from reliable traffic management sources.
Step 2	Data Organization	Deploy the given machine learning libraries and frameworks that support FNN and LSTM architecture, such as TensorFlow or PyTorch, to have an environment that is capable of performing deep learning.
Step 3	Software Setup	Install necessary machine learning libraries and frameworks that support FNN and LSTM architectures, such as TensorFlow or PyTorch, ensuring the environment is prepared for deep learning tasks.
Step 4	Data Preprocessin g	Data cleaning would ideally involve deletion of duplicated values and the treatment of missing values. Continuous input variables should be normalized to

		improve model performance and avoid model instability. Prepare the training, validation, and testing sets.
Step 5	Feature Engineering	Develop and select predictive features that are indicative of accident likelihood, such as rush hour flags, holiday indicators, or road type characteristics, enhancing the model's input with relevant contextual information.
Step 6	Model Configuratio n	Configure the individual FNN and LSTM models to have the right number of layers, neurons per layer, and activation functions that strike a balance between bias and variance.
Step 7	Parallel Model Training	The models would then be trained for both the FNN and LSTM on an individual basis on the training dataset itself, applying the batch approach with backpropagation to adjust weights for each network based on the historical accident data.
Step 8	Ensemble Integration	Combine in any form the results of FNN and LSTM models in a way that the combination makes it possible for the ensemble method to exploit the strength of each model in pattern recognition and temporal data analysis.
Step 9	Performance Evaluation	Validate the ensemble model using the validation set on measures of performance, such as accuracy, precision, recall, and F1-score, to evaluate the effectiveness of the model in identifying traffic accident predictions correctly.
Step 10	Optimization and Final Testing	Refine the model based on the feedback from validation, parameter tuning, and improving the ensemble strategy. Perform final testing on the unseen dataset so real-world applicability can be observed and robustness toward traffic accident detection can be seen.
Step 11	Deployment and Monitoring	Deploy the optimized ensemble model in an operational ITS environment, monitor its real-time performance, and iteratively improve it based on constantly updated results and the patterns of traffic evolution.

3.6 Evaluation Parameters

1. **Mean Absolute Error (MAE)**: MAE is the average magnitude of errors in a set of predictions while not taking into account their direction. It is calculated as the average over the absolute differences between the observed and predicted values. One would find it useful where the general value of the error—like traffic volume or speed—is important; for example, in traffic prediction, one [78].

$$MAE = \frac{1}{n}\sum_{i=0}^{n}\left|\hat{l_i} - l_i\right| \tag{3.1}$$

2. **Root Mean Square Error (RMSE)**: RMSE quantifies the average magnitude of error by squaring the differences between predicted and actual values, taking the means of those values, and finding the square root of it. RMSE is particularly appropriate in traffic forecasting models because it is very sensitive to any outliers that could lead to large errors and significantly affect system performance [77].

$$RSME = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2} \tag{3.2}$$

3. **R-squared (R^2)**: The coefficient of determination can be illustrated by R^2 as a statistical measure which features how much variance in the dependent variable can be predicted from the independent variables. A higher R^2 value for the ITS data approximates better model capability to explain variation on input size, such as weather conditions or time of day, in traffic pattern variation, be it accident frequency or traffic flow.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{3.3}$$

4. **Accuracy**: This metric measures the proportion of true results (both true positives and true negatives) among the total number of cases examined. For classification problems in ITS, such as detecting whether a traffic light is red or green, accuracy helps in assessing the overall correctness of the model [80].

$$Accuracy = \frac{True\ Positives + True\ Negatives}{True\ Positives + True\ Negatives + False\ Positives + False\ Negatives} \tag{3.4}$$

5. **Precision**: Precision is the ratio of true positive predictions to the total number of positive predictions made. In ITS, precision would be important for applications such as accident detection, where it is crucial that the positive detections are truly relevant (e.g., accurately identifying real accidents and not false alarms).

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Postives} \tag{3.5}$$

6. **Recall**: Recall, or sensitivity, measures the ability of a model to find all the relevant cases within a dataset. In the context of ITS, high recall would mean the model is effectively capturing most of the actual traffic incidents or conditions it's supposed to detect, such as identifying all pedestrian movements at crosswalks.

$$Recall = \frac{True\ Positives}{True\ Positive + False\ Negatives} \tag{3.6}$$

7. **F1 Score**: The F1 Score is the harmonic mean of precision and recall. It is a balanced measure that is used to test the accuracy of a classifier on a dataset for which true negatives don't matter much. In traffic systems, where both precision

and recall are crucial—for instance, in crash detection—the F1 score provides a single metric to gauge the overall performance of the predictive model [79].

$$F1\ Score = \frac{2 * (Precision * Recall)}{(Precison + Recall)} \tag{3.7}$$

CHAPTER 4

DEEP LEARNING MODELS AND ENSEMBLE MODEL

4.1 Support Vector Regression (SVR)

Support Vector Regression (SVR) plays a critical role in enhancing traffic flow and safety within Intelligent Transportation Systems (ITS) as discussed in the thesis. SVR, a derivative of Support Vector Machines (SVM), is employed for its robustness in performing regression tasks, particularly in estimating complex, non-linear relationships prevalent in traffic data. The methodology involves constructing a function that fits as many instances as possible within a pre-set error margin, ε, while simultaneously minimizing the model complexity, effectively striking a balance between the accuracy and generalization of the predictions.

Another important point where SVR is the good point for traffic management is the use of kernel functions to increase the dimensionality of the input data, which lets the linear regression model in that new space. Another evidence of its flexibility is the capability of being adjustable with different orders of traffic data dynamics [81]. It uses varied kernel functions like Polynomial, Linear, and Radial Basis Functions. These kernels help model such complicated patterns as the relations between volume, speed, and time of transportation, the knowledge of which is vital in predicting traffic conditions.

For the thesis, SVR was used to predict traffic density and velocity by applying it to predict the variables through the data collected from the sensors deployed across the transport networks. The predictions are now part of the thesis traffic management plan in advance, which would assist in timely action, like changing signaling timings, alert generation for a lower congestion, and reduced accident occurrences.

It optimizes the SVR parameters related to the penalty parameter C and epsilon margin with great care by using historical traffic data that enhances model performance. Cross-validation procedures assure that the model can be adapted to new traffic scenarios. This is a very illustrative example of a very tight training and validation process of a model, giving strong arguments for the model's capability to provide sound and useful predictions.

Integrating SVR into ITS, as outlined in the thesis, demonstrates its prime responsibility toward traffic control, which can lead to system improvement with respect to responsiveness and hence improvement in the safety conditions of the roads. With accurate predictions concerning trends in traffic, which lie within the aims of the thesis—in the application of advanced machine learning techniques—in solving practical problems facing transportation systems, SVR facilitates informed decision-making that will lead to smoother traffic flow and better road safety.

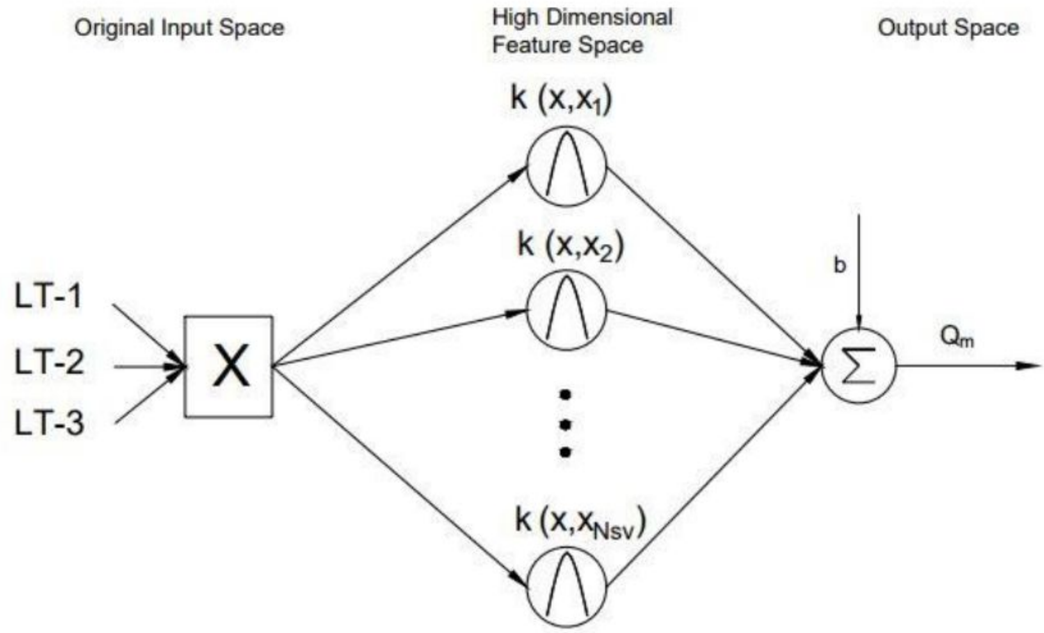


Fig. 4.1 Architecture of Support Vector Regression [82]

4.2 YOLOv8

YOLOv8 is a gigantic step in the direction of object detection based on the speed and performance that the "You Only Look Once" family brought to the system. This new version, YOLOv8, is equipped with complex neural network architecture and improved training methodologies with significant demonstrable improvements in performance over previous versions [83].

This makes speed and accuracy improvements highly optimal for real-time applications in the YOLOv8 architecture, respectively. The model is built on the underlying assumption whereby a whole image underlies the training and inference processing to predict the existence of a large number of objects with respect to their locations, just by a single forward pass [84]. It does so by running a fully convolutional neural network that divides the image into a grid of cells and predicts bounds and probabilities for each cell in the grid. Each cell predicts many bounding boxes and class probabilities together, which then goes through non-maximum suppression to become the final object detections.

A major strength of YOLOv8 is that it includes forward-looking convolutional layers, including changes in typical convolutional designs for better characteristic extraction, such that it results in better convergence by addition of nonlinearity and increases robustness at learning features using scales; it employs batch normalization and Leaky ReLU activations. Further, the YOLOv8 has attention processes and spatially pyramid pooling to boost the maps of features and centers of attention to major areas within the image, which are very important for grasping objects.

YOLOv8 is paramount to the verification and development of safety mechanisms by means of traffic monitoring under ITS. It should be strong in detecting vehicles, pedestrians, traffic infrastructure including signals and signs, even when being in the complex and dynamic scenes that traffic scenes characterize. Detection abilities should be very fast and highly correct for real-time applications, including adaptive traffic signal control, incident detection, and automated enforcement of traffic laws.

In addition, YOLOv8 is good with illumination and weather variance, different densities of traffic, making it, in fact, a very useful technology in the hands of ITS. With timely and reliable detections, the lay-up of advanced analytics to optimize the flow of traffic, manage congestion, and take predictive safety measures that then relate to the instances of congestion and accidents will be operational. These applications directly contribute to reducing traffic congestion and preventing accidents, thereby enhancing overall road safety and efficiency.

From the above facts, therefore, all advanced architectural configurations in YOLOv8 deployed in an ITS would easily meet the requirements for real-time and accurate object detection. This will contribute to a smarter, safer, and more responsive traffic management system, hence consistent with the goals for deployment of leading machine learning technologies to raise safety of transportation infrastructures.

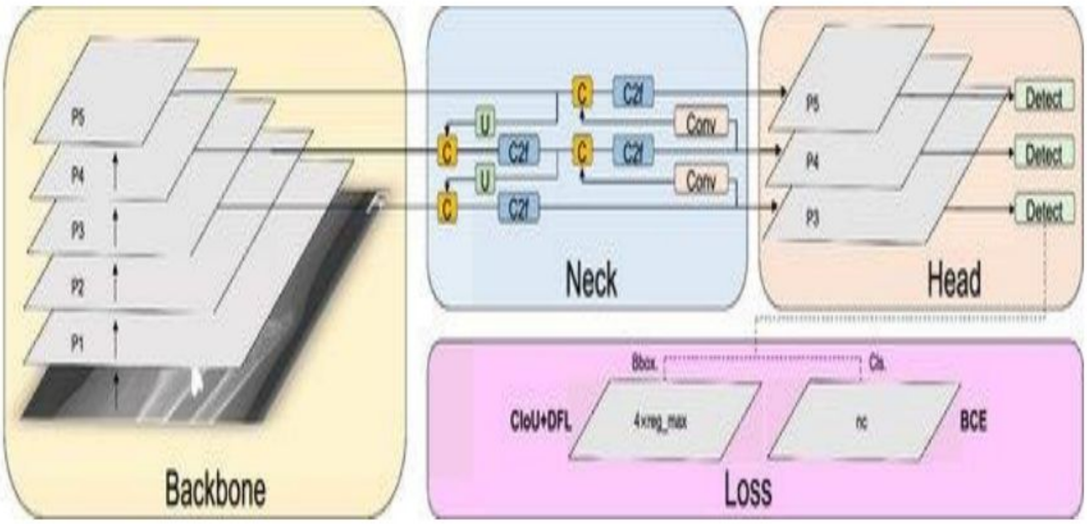


Fig. 4.2 Architecture of YOLOv8 [85]

4.3 Detectron2

Detectron2 is a newly developed advanced platform from the original Detectron framework. The software is generally used in works for object detection and image segmentation to recognize advanced and versatile modular designs that enhance flexibility and speed while being put to best use in various applications, including those of Intelligent Transportation Systems (ITS).

Detectron2 is a wrapper to be built on PyTorch, allowing it to directly interface with features and libraries of PyTorch in order to provide dynamic and effective training and deployment of models. This framework is strongly supported by a range of leading algorithms, such as Mask R-CNN, RetinaNet, and Faster R-CNN. For instance, the faster R-CNN uses region proposal networks (RPN), which share full-image convolution characteristics with a neural network, for real-time identification of objects, making it quite efficient. This, in turn, reduces the computation time and enhances the speed of detection. Internally, Mask R-CNN introduces some enhancements over Faster R-CNN: a branch to predict segmentation masks for each RoI. Combining these improvements with the high performance of Faster R-CNN, Mask R-CNN achieves state-of-the-art results on most of the instances, pixel-wise instance segmentation, which is very critical to object detailing in an image. RetinaNet has one up over its competition due to its tight loss function, which is accounting for the class imbalance in the training phase. This guarantees high recall in detecting objects over a complex visual environment and high class-class ratios.

The architecture for Detectron2 is meant to handle images with efficiency: advanced backbones of the neural network, such as ResNet and VGG, for feature extraction; this will be vital when trying to recognize numerous objects in a scene. These are further complemented by features like feature pyramiding and bounding box regression to enhance the accuracy and reliability of object detection.

The reason Detectron2 is likely to be useful in ITS is its strong object detection and segmentation, lying at the heart of improvements in traffic management and road safety. In general, Detectron2 can be put to use when analyzing video data from traffic cameras to detect and segment vehicles and pedestrians in this respect, together with other significant stuff, like traffic signs and lane-marking segmentation. Now, this will be critical data available to systems that are supposed to manage the flow of traffic, as knowledge to fine details about the exact location and movement of various entities on a road will be capable of causing dramatic effects on traffic control measures. For example, proper detection and segmentation of vehicles and pedestrians may assist in bettering phases of the traffic lights and pedestrian crossing time so that the number of congestions or accidents can be minimized with respect to the time factor.

Besides that, segmentation would greatly support Detectron2 in enhancing the detail when it comes to ITS in complex interactions of road users and environmental conditions. The high fidelity of visual analysis brought by Detectron2 supports the comprehensive construction of models of traffic scenes that support dynamic and automated decision-making in real-time traffic management systems. These functions directly support the overarching goals of improving traffic flow and ensuring safety, which correlate with strategic aims to make utilization of developed machine learning technologies for the purpose of smart networks with higher sensitivity [86].

Therefore, the architecture and functionalities of Detectron2 are technically designed for advanced object detection and segmentation, directly serving the practical objective of enabling the transformation of the monitoring and management of traffic environments.

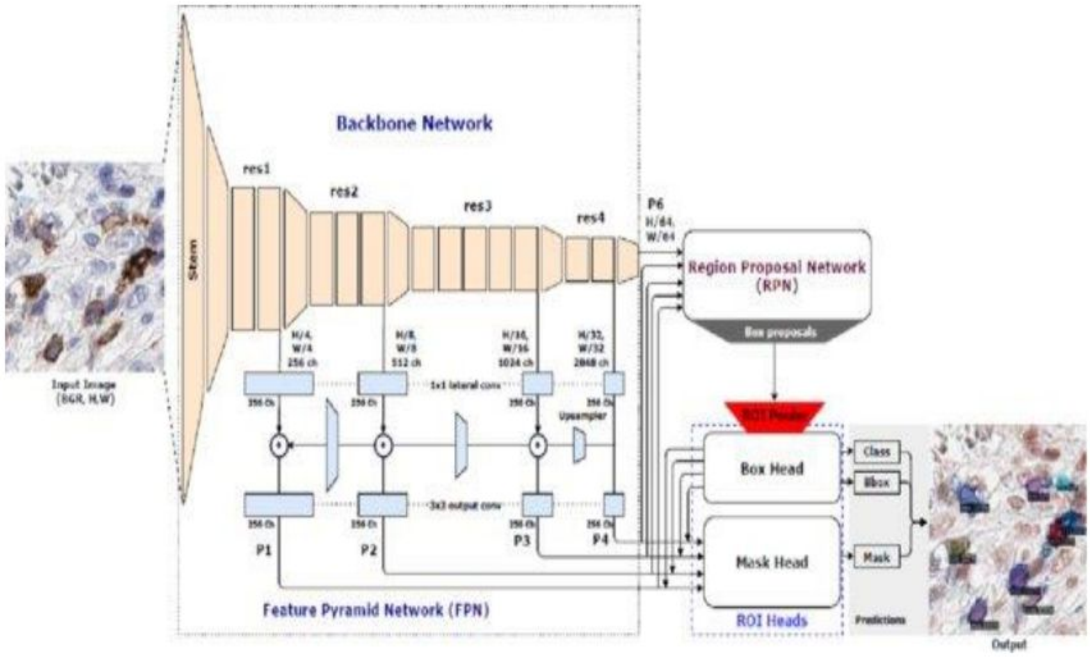


Fig. 4.3 Architecture of Detectron2 [87]

4.4 Ensemble model of YOLOv8 and Detectron2

The ensemble model of the state-of-the-art YOLOv8 model and Detectron2 for use within an ITS application is presented. The proposed hybrid model harnesses the fast object detection capabilities of YOLOv8 and presents a high level of image segmentation accuracy such that it offers an effective system for traffic flow and safety improvement. It integrates two technologies in such a way that a model that copes with the utmost necessities of ITS—low latency and high precision in understanding the environment—is realized [88].

With the use of this, YOLOv8 performs well in various object detection across the entire scene very fast, making it relevant to real-time tasks and corresponding closely with the adaptive traffic light systems and urgent response mechanisms. This guarantees a quick and reliable identification of vehicles, pedestrians, and traffic signs, even in rather complex traffic scenarios. Additionally, the Detectron2 enables a more fine-grained analysis in the sense that it effectively segments the detected objects, allowing the possibility of granular traffic environment assessment—for example, "determination of when overlapping vehicles are happening during peak traffic period" or "assessment of the visibility and condition of road markings and signs under different weather conditions".

The ensemble model, YOLOv8, and Detectron2 are individually fine-tuned first on large datasets that represent a large number of traffic scenarios. These are difficult datasets for the models, as they all come under different lighting, weather, and traffic conditions to guarantee that the final system can work accurately and dependably in different environments. After individual training, the models are merged and act as a combined system, while each model fine-tunes for optimization in terms of harmonization of detection and segmentation functions to enhance the complementary force of both.

Ensemble model performance will be evaluated based on the mixture of precision, recall, f1-score, processing speed, and segmentation accuracy. The first three are important in affirming that the model is appropriate to be deployed in ITS because proper speed and accuracy are among the key components in effective management of smooth movement in traffic together with safety measures.

The ensemble model provides all-round traffic analysis in practical ITS applications with embedded capabilities for control against congestion, dynamism enhancement in traffic flow, and improved management of incidents. These include accurate automated toll collection and enforcement of laws on the movement of vehicles through cities. Consequently, this ensemble model will meet and even push forward the goals of the thesis to show how the integration of state-of-theart machine learning technologies can drastically enhance the overall effectiveness of Intelligent Transportation Systems.

4.5 YOLO-NAS

The YOLO-NAS (You Only Look Once - Neural Architecture Search) is a state-of-the-art innovation specifically designed to bring machine learning in the evolution of advanced object detection, especially in ITS. The traditional YOLO series is engineered to a great extent in this model by integrating neural architecture search techniques for network structure optimization to enhance the detection accuracy and processing efficiency [89].

YOLO-NAS is built upon the insight of the YOLO framework, which has been well-appreciated for its rather huge capability of performing instant and real-time object detection through the process of viewing an entire image at a glance [90]. This is attained by segmenting an image into a grid so that there can be simultaneous inferences drawn from the predictions of bounding boxes and class probabilities of this grid cell. What sets YOLO-NAS apart is the application of AM to optimize, in a principled and targeted manner, the YOLO framework architecture. The technique applies reinforcement learning, but with a controller network that loops over candidate architectures to be evaluated; the found architectures are applied for traffic object detection.

NAS is integrated to get YOLO-NAS into an adaptive fashion that dynamic structures adapt in the quest for both speed and accuracy, which are always significant for real-time applications in ITS. For instance, it can vary the depth of convolutional layers, the number of filters, or the connections between those layers to support the computational limits and performance requirements of traffic management systems. This ensures that YOLO-NAS is light enough in abstraction to be deployed and still serve its intended purpose in edge devices—either as traffic cameras or onboard vehicle systems for the infrastructure of ITS—while maintaining very high accuracy in detecting objects.

However, the developed detection capabilities of YOLO-NAS are very critical to ITS applications. It enhances the monitoring of traffic by detecting and classifying important objects within a traffic scene: vehicles, pedestrians, among others. That level of object recognition is important for enhancing the performance of systems responsible for traffic density evaluations, enforcement of traffic laws, and observing potential risks on roads. Real-time and accurate data from the traffic environment enable YOLO-NAS to support automated decision-making processes that enhance flow while reducing congestion. This makes it safer for navigation aids in autonomous driving systems, which usually require some accurate understanding of one's surroundings because of the subtle and complex elements of the traffic captured.

Other important qualities that make YOLO-NAS invaluable to ITS are its robustness in varying operational conditions, buttressed by different lighting and weather situations. Deployment of YOLO-NAS also can lead to some very important improvements in the effectiveness of traffic management strategies; for example, optimization of signal timing based on actual traffic conditions and even improvements in emergency response strategies during traffic incidents. In this regard, YOLO-NAS contributes forthrightly to what ITS as a policy aims to achieve, namely, safer and more effective urban mobility solutions.

Thereby, YOLO-NAS is far more than just a neural network frontline in terms of design; it is the cornerstone for making more advances in Intelligent Transportation Systems and it harnesses the latest in machine learning technology to deal with modern challenges in traffic management and with ensuring road safety.

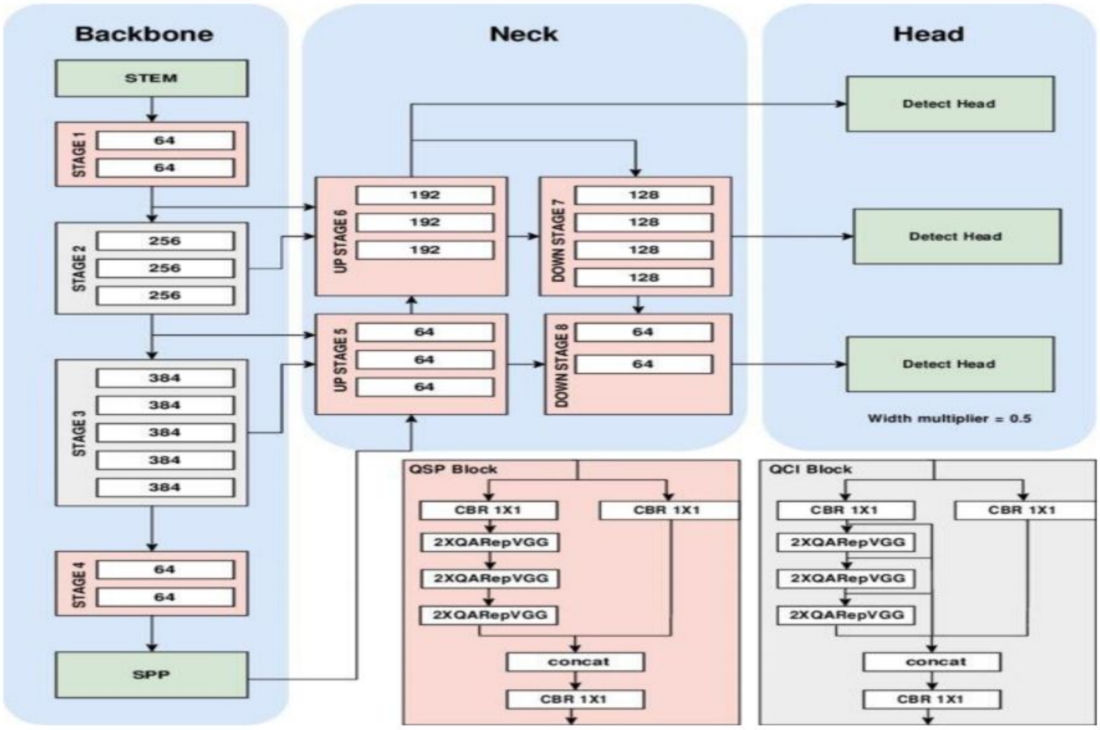


Fig. 4.4 Architecture of YOLO-NAS [91]

4.6 Mask R-CNN

The influential model in computer vision is Mask R-CNN, which demonstrated accuracy when the object segmentation within complex pictures was required. Mask R-CNN is an expansion of the Faster R-CNN, state-of-the-art object detection model, with the addition of a delineation algorithm that moves beyond the bounding box to recognize objects in an image and generate high-fidelity masks outlining each object found [92]. Because of this capability, therefore, Mask R-CNN is very promising for applications in Intelligent Transportation Systems (ITS), in which exact space evaluation in traffic scenarios is relevant to expanding safety- and traffic management-measure applicability.

Uniqueness in the Mask R-CNN architecture lies in the two-step architecture: at the first stage, it uses RPN, which makes a pass over the image and gives proposals about regions that might bound an object; and in the second step, these proposals are refined, but a distinction from other detection models happens: items in each region are identified, all while creating a pixel-level mask. This step introduces an additional parallel branch into an existing Faster R-CNN model, where the mask branch constructs pixel-by-pixel segmentation masks using small and fully convolutional networks for each region of interest. As a result, Mask R-CNN can achieve not only speedup in detection but also precisely pixel-level one-shot segmentation in just a single forward pass of networks.

Integration of Mask R-CNN within the ITS harnesses the detection and segmentation capability of the network, bringing about a great increase in system functionalities regarding traffic monitoring and control. The detailed segmentation obtained from the use of Mask R-CNN in the ITS allows for accurate and real-time tracking of vehicles, pedestrians, and other elements like traffic lights and signs. It also assists in more accurate object partitioning and understanding the flow of traffic in terms of vehicle spacing, pedestrian densities, and congestion—factors that all become very critical for removal with the danger of collision. Moreover, the splitting and identification of different road users and obstacles make the system capable of handling more advanced autonomous driving functionalities with interventions kept to a minimum for the commitment of a safer driving environment.

Also, Mask R-CNN is robust in handling diverse and challenging visual scenarios such as variable lighting, weather conditions, occlusions, etc., which makes this valuable for use in an ITS. The capability of correctly adjudicating complex scenes underlies the reliability of performance over a wide array of conditions—a very critical job that necessitates consistent operation, especially in changing environments and times.

It is further refined in this line by making use of Mask R-CNN, which refines the operational intelligence of an intelligent ITS system so that the latter can make better, informed decisions to allow improved, safer, and more efficient traffic flow. Accurate object detection and segmentation lead to insights by which the development of traffic management strategies becomes more efficient [93]. For example, dynamic lane management and the use of predictive traffic signalling help reduce traffic congestion and ensure road safety. Thus, it also meets the objective of this thesis in solving practical problems related to transportation systems by cutting-edge machine learning.

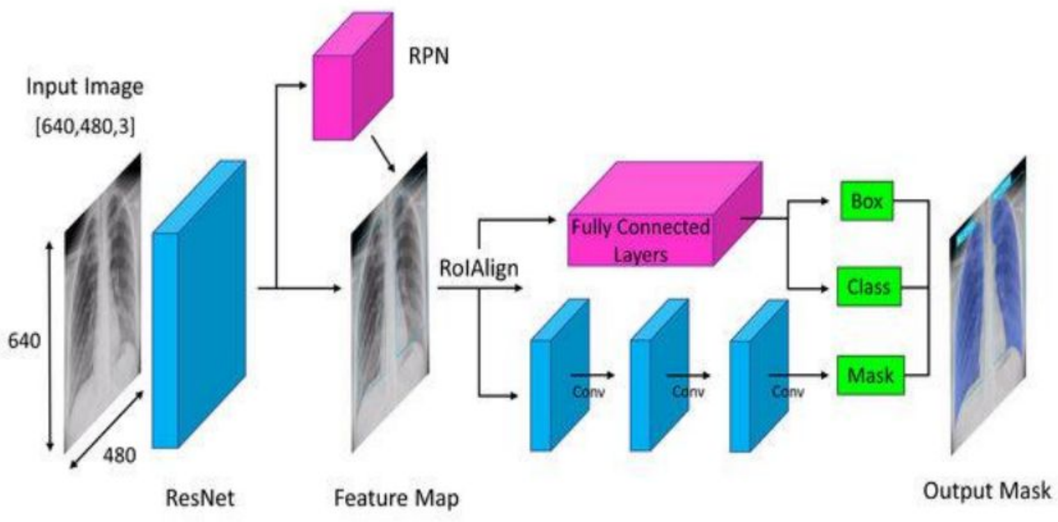


Fig. 4.5. Architecture of Mask R-CNN [94]

4.7 Ensemble of YOLO-NAS and Mask R-CNN

The ensembled model integrates Mask R-CNN and YOLOv8 techniques, therefore a revolution in applying these machine learning methods is a synergy in results improvement [95]. Into this hybrid model are combined the efficiencies of Mask R-CNN, which has very precise skills in object segmentation, and YOLOv8, which is very useful in object recognition and is very fast and accurate. Finally, when the combined models are put together, they make a complete system well defined to distinguish and outline complex traffic scenes from different elements; therefore, it becomes invaluable for ITS application.

YOLOv8 acts as the first detector in the ensemble. Its design aims to rapidly scan all scenes and come up with a prediction over many objects, including cars, pedestrians, and traffic signs. The technical importance of this part of the ensemble is very great if it is meant to be operational in real time, since there will be great importance regarding exactly how soon results can be seen for the sake of response to changing traffic situations. The processing speed of YOLOv8 can be made very fast to ensure an ensemble model that is capable of operating with real-time performance in high-traffic scenarios through making quick decisions, which may contribute or detract from the flow and security of traffic.

Mask R-CNN enhances the detections made by YOLOv8 by adding a segmentation mask to each detected object. Such features would enable the pixel-level definition of object boundaries, which proves very essential in tasks requiring an understanding of spatial relationships down to very fine details—like the ability to tell vehicles that are very near to each other apart or to make it easier for lane markers to be detected. Mask R-CNN works based on the regions proposed by YOLOv8 and refines them further. Now, it's not just possible to establish whether or not an object is there, but indeed the proper shape and extent within the context of the visible field can actually be grasped.

The combination of YOLOv8 and Mask R-CNN brings the best of the best individually: YOLOv8 for the speed of detection and Mask R-CNN for highly detailed segmentation. This synergy enriches ITS with dual layer analysis in terms of rapid detection followed by detailed segmentation. For instance, these models work very well in adaptive traffic control systems since, in this case, the context of the scene can be used to alter the setting of the traffic lights and drive down particular lanes. Moreover, the detailed output that comes from the ensemble contributes to the systems used for the navigation of the latter; if precise information arises, then road conditions, presence of obstacles, and other road users are detected for safe operation [96].

By implementation, the combination reaction of YOLOv8 and Mask R-CNN is not just an improvement in terms of real-time functionality but also comes with long-term traffic management strategies. The model efficiently ensures road systems and urban areas are safe through accurate analysis of the traffic patterns and behaviors.

Besides, this integration of multi-models into the operation of an ITS shows how advanced machine learning techniques might effectively change the operation of traditional traffic systems to produce a smarter, safer, and more responsive infrastructure. Closer to the key thesis goals is this in support of cutting-edge technology being applicable for increased traffic flow and safety—evidence that YOLOv8 and Mask R-CNN are not just theoretical advancements but a practical solution to the problems impeding modern transportation.

4.8 Feedforward Neural Network

The correct approach, therefore, is used when implementing a feedforward neural network in the context of enhancing traffic flow and safety at ITS using machine learning. Artificial neural networks offer a really simple yet strong mechanism for pattern recognition tasks, which are basic to processing and interpreting any kind of traffic effectively.

A typical feedforward neural network consists of an input layer, a hidden layer (or layers), and an output layer with neurons in each. We then fine-tune these weights—meaning the connections between the neurons in one layer and those in another—with a view to minimizing prediction error [97]. The term "feedforward" network refers to the fact that the data all go in one direction—from the layer that receives it to the output layer—through the hidden layers.

Practically, FNNs applied in ITS are used to analyze an assortment of input variables that may include traffic densities, speeds, and patterns among various times and conditions. Such inputs, fed to the network, enable an FNN to learn and identify hidden complex patterns and relationships that might not be apparent quickly. For example, it can even predict traffic jams with only current traffic inputs in combination with historical data.

In addition, FNNs have the power to approximate any function with a very high degree of approximation if the number of neurons and layer is good on their part, which gives them notorious versatility in handling various prediction tasks that ITS must know: from forecasting traffic volumes to estimating the potential of accidents at different road segments [98]. For example, depending on the ITS requirements, the output layer may either be specialized to produce binary outputs through the layer for such cases as "a high risk against low risk of accidents" or continuous outputs through the layer for prediction on traffic speed.

IT can, therefore, make such traffic management systems better by providing data-driven insights that support dynamism through the incorporation of FNNs. For example, ITS predicts that, during the peak of traffic and where a hot spot for congestion is expected, necessary changes in the signal timing or a warning to the drivers about alternative routes will be made dynamically so that the flow of traffic is improved, and congestion and accidents are avoided. Moreover, a predicting capability of traffic patterns supports the ability to match long-range planning and set related strategies for road network improvements and adjustments in public transport.

Ultimately, ITS using feedforward neural networks exemplifies the manner in which machine learning technologies can be utilized for improvements not only in terms of efficiency but also with regard to safety in traffic systems. FNNs act as key elements that will make transportation networks smarter and responsive through the transformation of raw traffic data into intelligent and meaningful information that can be acted upon, thus completely instrumenting the first objective of the thesis—to leverage advanced data-driven machine learning techniques for improving traffic flow and safety.

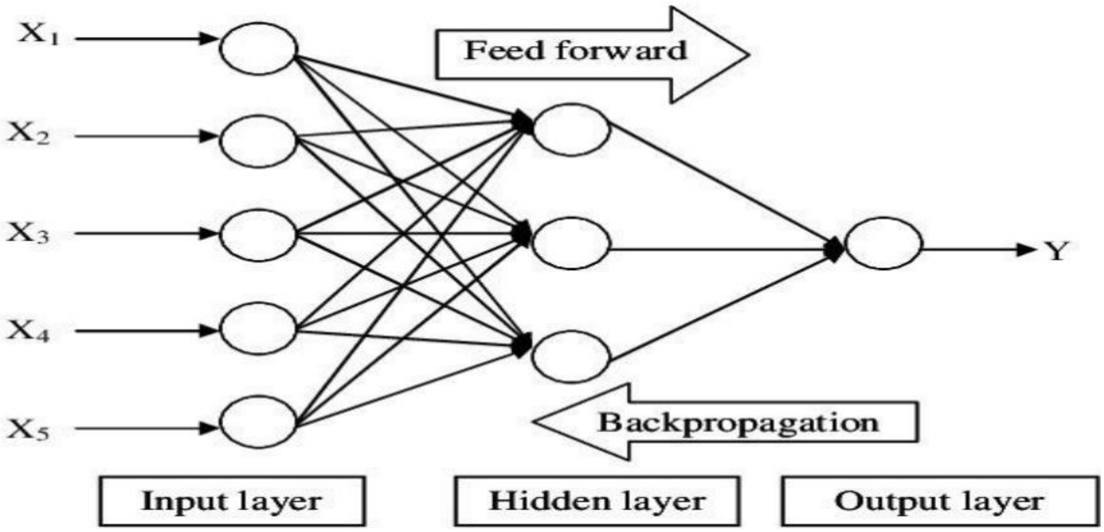


Fig. 4.6 Architecture of Feed Forward Neural Network [99]

4.9 Long short-term Memory (LSTM)

Long Short-Term Memory (LSTM) networks are a special class of RNN, useful for the solution of sequence prediction issues, which are essential in improving traffic flow and safety in ITS. These LSTMs can be able to deal with sequential data compared with standard feedforward neural networks, making them appropriate with time-based data, such as those typical in traffic patterns, wherein past information is key for driving future conditions [100].

This helps LSTM networks to avoid the issue of the vanishing gradient, which plagues classical RNNs, through the use of a central design with many memory cells capable of maintaining a state over time. It is this three-gate architecture—consisting of an input gate, a memory gate, and an output gate—that allows an LSTM to do that. They include: • Input gates: These regulate the amount of new values that can flood into the cell. • Forget gates: They determine what part of information from the past states can be enjoyed. • Output gates: Indicating what is to be output. In conclusion, LSTMs are very useful for applications that need a memory of data from long ago, for instance, traffic volumes and speed trends over time.

In the context of ITS, LSTMs are used for modeling and predicting traffic conditions over time. Given past traffic data, LSTMs can make predictions for future traffic states, which include the status of the road network, among many other details not listed here. Such predictions are critically important for effective real-time practical traffic management systems in making decisions regarding the alteration of timings of traffic signals, deploying staff for traffic management, and activating dynamic message signs to guide driver behavior. For example, using LSTMs, preemptive interventions could be made in peak traffic hours within an ITS to relieve congestion and improve road safety before it gets worse.

Further, LSTMs contribute to the safety part of ITS through activity such as analysis of sequences of traffic incidents in the prediction of conditions leading to accidents. Typical traffic densities or recurring times during the day, along with associated weather conditions that lead to an accident, are understood and, thus, LSTMs help the ITS to pick out risk patterns and let safety measures follow one another proactively [101].

In general, the application of LSTM networks in ITS frameworks reveals how advanced machine learning techniques help to enhance the efficiency and safety of transportation systems. With the exploitation of the capability of LSTMs for modeling the temporal dynamics, the system is able to respond more dynamically not only to the immediate traffic situation but also in the planning and controlling strategies, which anticipate potential future statuses, leading to safer and more fluid traffic environments. This aligns well with the ultimate purpose of applying the most advanced machine learning technologies in solving practical transportation problems and signifies that the contributions from LSTMs will be in fostering systemic improvements for management and safety across traffic.

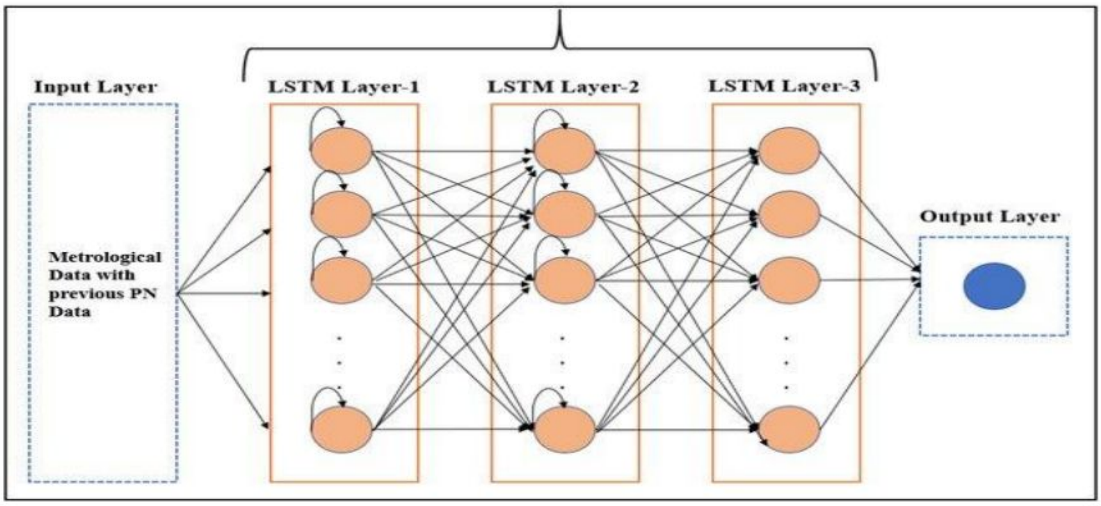


Fig. 4.7. Architecture of LSTM [102]

4.10 Ensemble of FNN and LSTM

An ensemble model based on Feed Forward Neural Networks and Long Short-Term Memory networks is a new way which helps boost the predictive ability of an Intelligent Transport System. The model is a hybrid, making an integrated unique strength found in conventional FNN capable of capturing any relationship or set of relationships between the independent variables while considering the outputs and LSTMs, which are good recognizers of temporal patterns and dependencies.

The FNN part of such an ensemble architecture is configured to appropriately handle spatial features and static data points that exist in the environment, such as distances between vehicles, type of vehicle, road signs, and barriers. This makes it possible for the model to quickly interpret the current state of traffic, therefore providing instantaneous evaluations based on the visible environmental conditions.

This LSTM element handles the incorporation of time dependencies into features such as speed trends, traffic flow rates across the day, and historical accident data. Since an LSTM intrinsically represents a sequence, prediction based on learning from past trends in the sequence can be easily carried out, rendering them highly suitable to predict future traffic conditions. Information contained within the LSTM layers across the sequences gives it a memory function for tracking evolving traffic patterns. It is this power of predictivity on the future state that it gains from the fact that it has a memory of the different oscillations in which we are trying to predict the future state.

The first type of neural network characterizes the ensemble model to use FNN's property of modeling relationships that are not temporal and harnessing the power of LSTM in the sequence prediction. The resultant amalgamation of the two could lead to intensive data analysis in terms of improved predictive performance and robustness. The end output is combined in both types of networks. Mostly, this is done by a layer called the merging layer. The merging layer would combine the insights from the spatial and temporal analyses into one single prediction.

It's a kind of transformational application that directly applies to ITS through an ensemble model, allowing much better fine-tuned control over traffic management systems. For instance, it would be in a good position to predict the traffic volumes and potential congestion points based on the current traffic state and further historical data trends, enabling the traffic controllers to stay ahead in their signal adjustments or dispatch messages proactively for the diversion of traffic in order to enhance flow and lower risks of congestion. Besides, it can hugely reduce the potential for incidents and increase road safety because ITS can establish preventative safety measures since it can predict better than the current accident-prone conditions.

The fusing of FNNs with LSTMs in an integrated ensemble model for ITS provides a robust framework for real-time and predictive traffic management [103]. It corresponds fully to what has already been defined as a purpose—an effective solution for the complex real-world problem by using advanced machine learning technologies in order to raise levels of flow and traffic safety. The ensemble model not just acts upon the current status but also tries to predict the future, hence making traffic and safety management proactive in approach.

CHAPTER 5

RESULTS AND DISCUSSION

This section presents and discusses the results of the proposed machine learning models, focusing on four key areas essential for enhancing traffic flow and safety in Intelligent Transportation Systems (ITS). Each subsection addresses a specific problem, providing detailed analyses and insights derived from the respective models. The subsections are organized as follows:

5.1 Traffic Prediction

This next portion of this thesis evaluates concrete machine learning models in traffic prediction—a highly critical constituent of the general aim to increase traffic flow and safety within ITS. Correctly predicting traffic leads mainly to overcoming congestion, effective traffic management, and road safety directly, which in itself allows an ITS to operate correctly and dependably.

Table 5.1 The PEMSD4 and PEMSD8 performance evaluation of multiple methods.

Models	**PeMSD4**		**PeMSD8**	
	MAE	***RSME***	***MAE***	***RSME***
LSTM	29.45	45.82	23.18	36.96
STGCN	25.15	38.29	18.88	27.87
GeoMAN	23.64	37.84	17.84	28.91
MSTGCN	22.73	35.64	17.47	26.47
ASTGCN	21.80	32.82	16.63	25.27
SVR	**19.21**	**30.57**	**13.87**	**22.76**

Performance analysis of models performed with architectures such as Long Short-Term Memory (LSTM), Spatio-Temporal Graph Convolutional Networks (STGCN), Geo-spatial Temporal Attention Network (GeoMAN), Multi-Spectral Temporal Graph Convolutional Network (MSTGCN), Attention Based Spatial-Temporal Graph Convolutional Networks (ASTGCN), and Support Vector Regression (SVR) are worked on. These have been tested on PeMSD4 and PeMSD8 datasets, whereby the benchmark datasets are highly essential for the evaluation of a good predictive model in a real-world scenario.

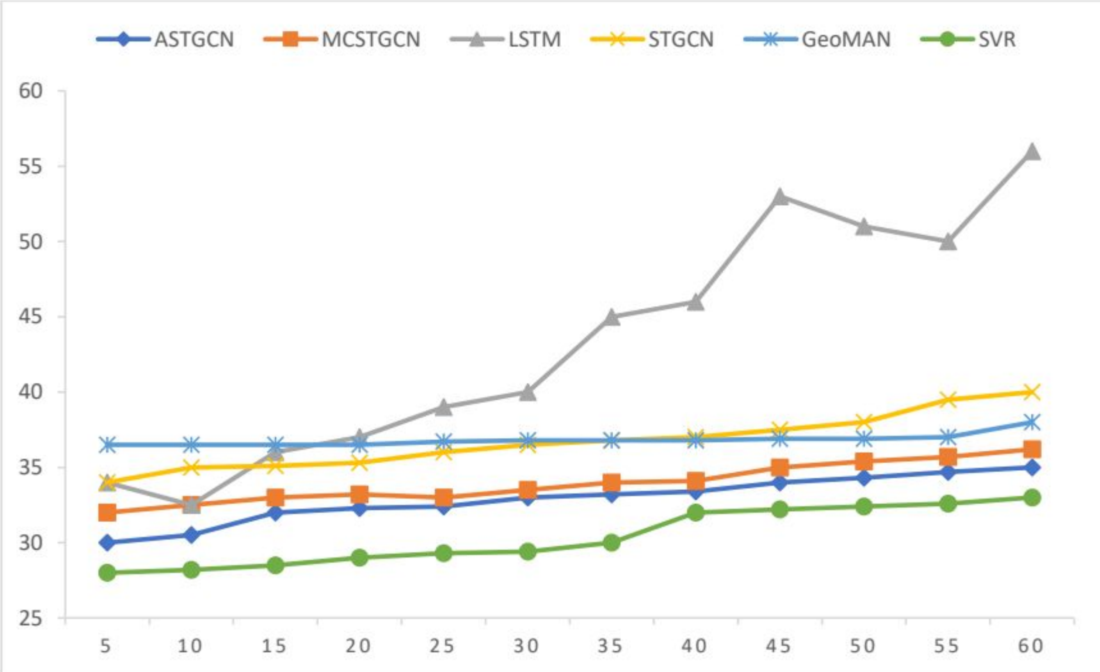


Fig. 5.1 RMSE graph for several techniques on PeMSD4.

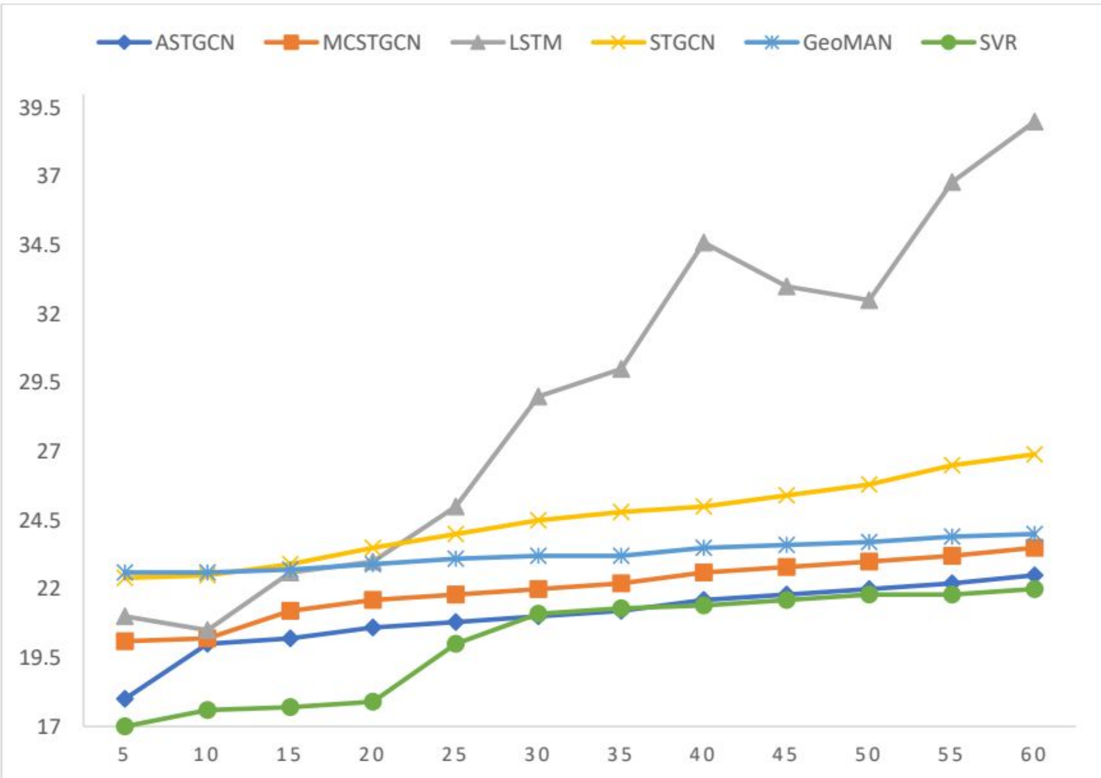


Fig. 5.2 MAE graph for several techniques on PeMSD4.

The evaluation was carried out on the two basic measures provided for each model: MAE and RMSE. It gives the predictions, which will be some estimates of error and reliability. We can clearly see that the SVR technique has efficiently performed using both datasets and minimized the MAE and RMSE of the predictions. The results are plotted in elaborated graphs showing the model performances over time, where emphasis is placed on trends and the capability to handle traffic data complexity.

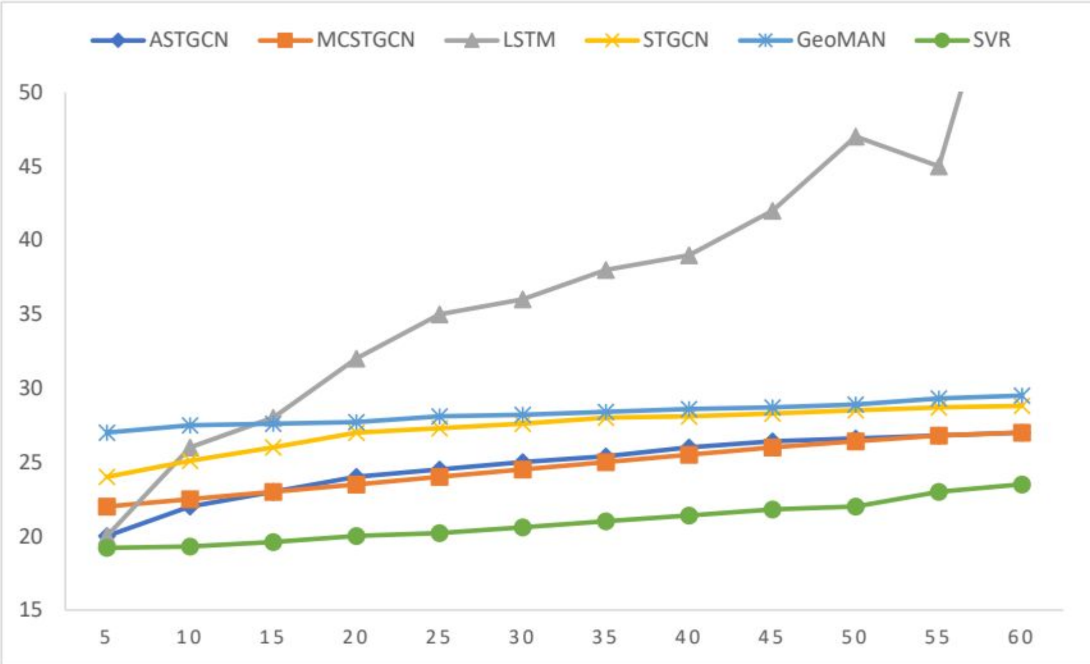


Fig. 5.3. RMSE graph for several techniques on PeMSD8.

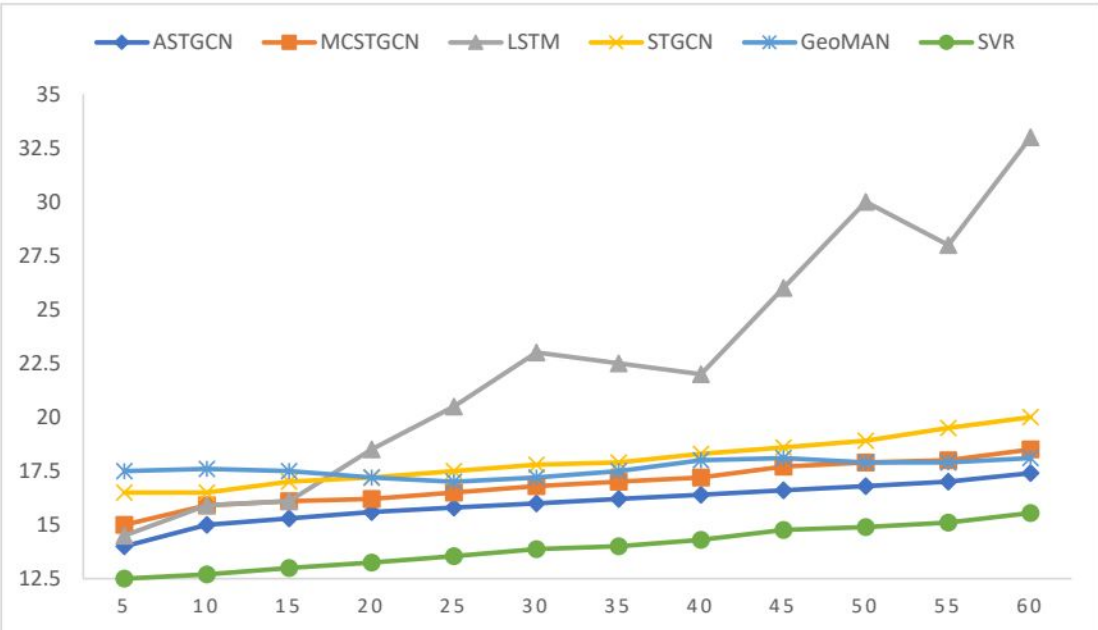


Fig. 5.4. MAE graph for several techniques on PeMSD8.

Table comparing different machine learning models under traffic prediction on two datasets: PeMSD4 and PeMSD8. The listed models are Long Short-Term Memory, Spatio-Temporal Graph Convolutional Networks, Geo-spatial Temporal Attention Network, Multi-Spectral Temporal Graph Convolutional Network, Attention Based Spatial-Temporal Graph Convolutional Networks, and Support Vector Regression. Now, the performance metrics measuring the accuracy and reliability of the models are the MAE and RMSE; the outcome here showed that in this regard the SVR outperforms all other models by far because it attains the least MAE and RMSE scores on both datasets: PeMSD4. This signifies SVR as a better method for producing predictions on traffic conditions with better accuracy and more consistently, hence it provides an answerable use for strong potential improvement in Intelligent Transportation Systems regarding flow and safety in traffic.

5.2 Traffic sign board prediction

This part of the thesis focuses on the application of an advanced ensemble model, combining YOLOv8 and Detectron2, for traffic sign board prediction—a crucial step in enhancing traffic flow and subsequently ensuring safety within ITS. This model is part of our broader goal to include machine learning in the ITS, which is going to solve more complex traffic management issues, including accurate and reliable traffic sign detection forming an essential part of automated driving systems and driver support technologies.

Table 5.2 Analysing the performance of present models across GTSRB, BTSD

Datasets	GTSRB			BTSD		
Models	Precision	Recall	F1 Score	Precision	Recall	F1 Score
RCNN	95.2	95.0	95.1	96.7	96.5	96.6
SPPNet	98.2	98.3	98.2	93.6	94.2	93.9
Fast RCNN	98.8	98.7	98.7	97.2	97.0	97.1
R-FCN	98.5	98.6	98.5	94.8	95.2	95.0
Transformer (ViT)	98.6	98.4	98.5	95.2	95.0	95.1
SSD: Single Shot MultiBox Detector	98.6	98.5	98.7	96.7	96.5	96.6
RetinaNet	98.8	98.7	98.7	97.2	97.0	97.1

Ensemble (YOLOV8 + Detectron2)	99.2	99.4	99.3	98.5	98.9	98.7

Table 5.3 Analysing the performance of present models across STSD, ITSD

Datasets	STSD			ITSD		
Models	Precision	Recall	F1 Score	Precision	Recall	F1 Score
RCNN	95.9	95.7	95.8	95.6	95.4	95.5
SPPNet	97.1	97.3	97.2	96.7	96.9	96.8
Fast RCNN	98.5	98.4	98.4	98.2	98.1	98.1
R-FCN	97.4	97.6	97.5	97	97.2	97.1
Transformer (ViT)	98.1	97.9	98	97.4	97.2	97.3
SSD: Single Shot MultiBox Detector	97.9	97.7	97.8	97.5	97.2	97.3
RetinaNet	98.5	98.4	98.4	98.2	98.1	98.1
Ensemble (YOLOV8 + Detectron2)	97.8	98.2	98	99.2	99.1	99.1

The performance of the ensemble model is estimated over significant existing datasets in the domain, which include German Traffic Sign Recognition Benchmark (GTSRB), Belgian Traffic Sign Dataset (BTSD), Swedish Traffic Sign Dataset (STSD), and Indian Traffic Sign Dataset (ITSD). A variety in these datasets in terms of different sign types and real-world conditions is opted to be really effective and fitting as a comprehensive testing ground for the effectiveness of the model. Key evaluation metrics in use include precision, recall, and F1 score, measuring the rate at which a model will be helpful or reliable in identifying and classifying traffic signs.

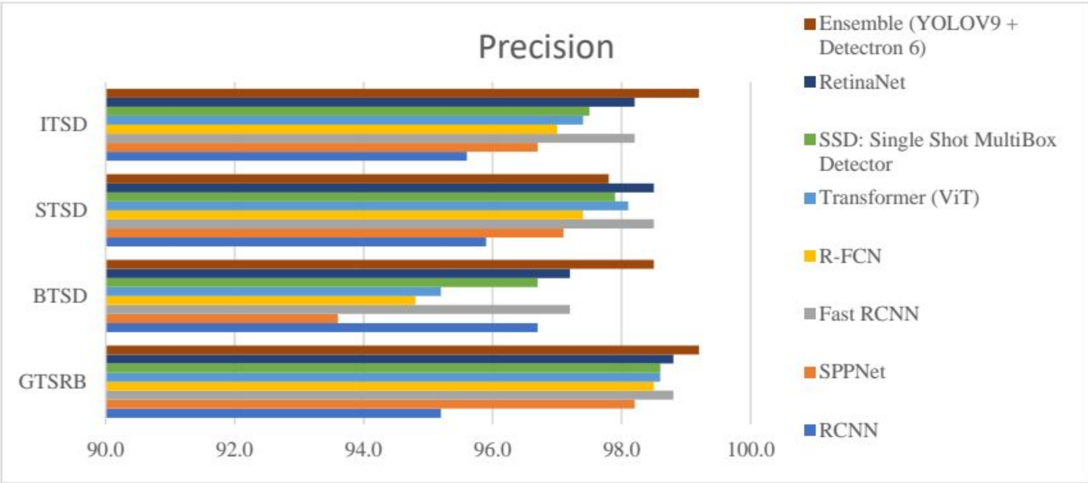


Fig. 5.5 Precision for various models on ITSD, STSD, BTSD, GTSRB

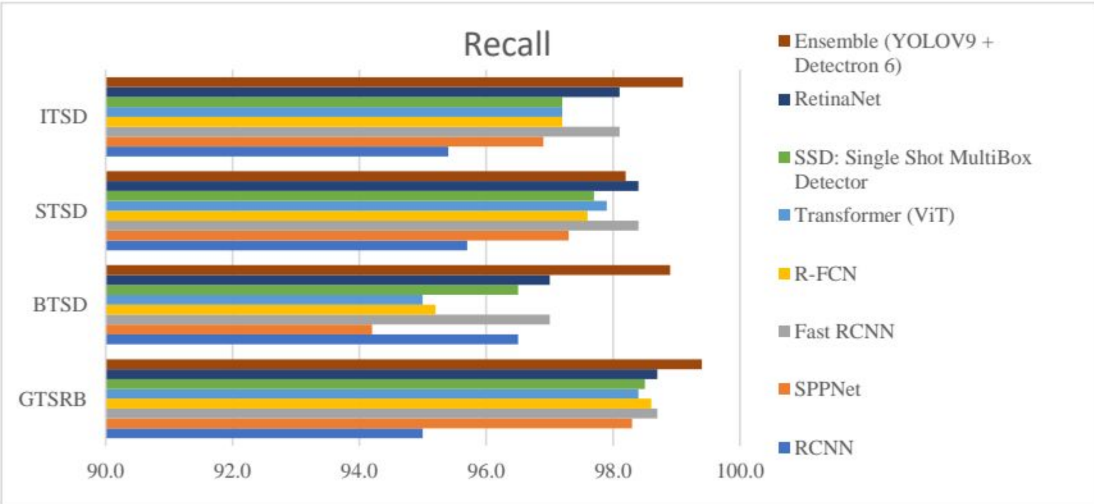


Fig. 5.6 Recall for various models on ITSD, STSD, BTSD, GTSRB

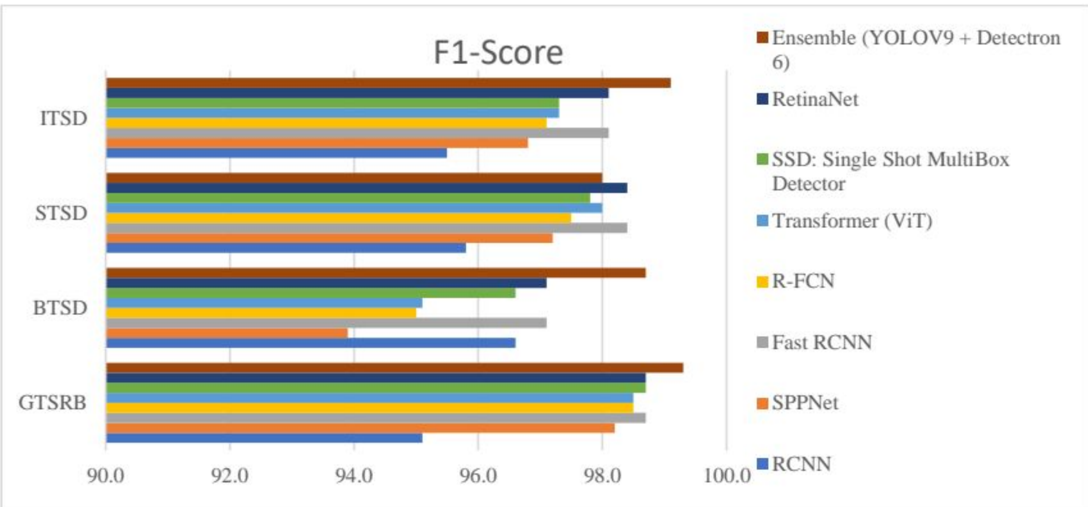


Fig. 5.7 F1-Score for various models on ITSD, STSD, BTSD, GTSRB

Extensive comparative evaluation is performed with various state-of-the-art models, which comprise the RCNN, SPPNet, Fast RCNN, R-FCN, Transformer (ViT), SSD (Single Shot MultiBox Detector), and RetinaNet in an emphasis on efficiency offered by our ensemble approach. The YOLOv8 and Detectron2 ensemble, of course, is the one showing the highest performance since a higher score points toward the better role played by the ensemble in catching the more complex details necessary for exact traffic recognition.

The table elaborately compares the various machine learning models utilized for recognizing traffic signs on four different datasets: German Traffic Sign Recognition Benchmark (GTSRB), Belgian Traffic Sign Dataset (BTSD), Swedish Traffic Sign Dataset (STSD), and Indian Traffic Sign Dataset (ITSD). This is further illustrated to show how each model performs with Precision, Recall, and F1 Score. The ensemble YOLOv8 with Detectron2, in particular, outperforms the others. It can provide the best scores, especially on all datasets. For example, this model managed to reach a precision of 99.2%, recall of 99.4%, and F1 score of 99.3% at GTSRB. These metrics are crucial and vital to measure the accuracy and reliability of every model in detecting and classifying traffic signs correctly, so they have potential for improvement in the flow and safety of traffic in Intelligent Transportation Systems. Excellent indications are provided by the outstanding performance of the ensemble model with respect to the robust capability of an ensemble model to successfully perform many diverse and difficult tasks involved in the area of traffic sign recognition, which is importantly useful for real-time decision-making in the ITS application.

5.3 Traffic Light Detection

This subsection details an evaluation of an advanced ensemble architecture that combines the Yolo-NAS and Mask R-CNN models, particularly designed for making predictions of traffic light states. This underpins a critical system in an attempt to make intelligent transport systems with the most sophisticated machine learning methods as far as traffic flow and general road usage are concerned. Accurate traffic light predictions should be based on the optimization of the control of traffic in a way that smooths the flow and guarantees safe and suitable travel, considering the complex landscape of urban scenarios.

Table 5.4 Comparative Performance Metrics of Various Models

Models	mAP*	mAR*	F1 Score
Faster R-CNN	0.765	0.778	0.795
EfficientNet-B3	0.434	0.422	0.428

RetinaNet	0.717	0.69	0.703
YOLO V8	0.73	0.681	0.705
Yolo-NAS	0.755	0.713	0.733
Mask R-CNN	0.788	0.731	0.758
Ensemble	0.843	0.787	0.814

***IoU >= 0.5**

Table 5.5 Class-Level Precision and Recall of Mask R-CNN and Ensemble YOLO-NAS Models

ClassID	Name	Total	Precision*	Recall*
0	stopleft	4239	0.748	0.843
1	goleft	872	0.782	0.849
2	warningleft	126	0.877	0.733
3	go	15563	0.881	0.789
4	warning	958	0.794	0.716
5	stop	14682	0.837	0.77
6	goforward	94	0.76	0.731

***IoU >= 0.5**

The performance of the ensemble model, along with other leading models such as Faster R-CNN, EfficientNet-B3, RetinaNet, and YOLO V8, is meticulously analyzed. The key metrics used to assess these models include Mean Average Precision (mAP), Mean Average Recall (mAR), and the F1 Score, which collectively provide a comprehensive view of each model's accuracy, reliability, and overall effectiveness in recognizing and interpreting traffic light signals.

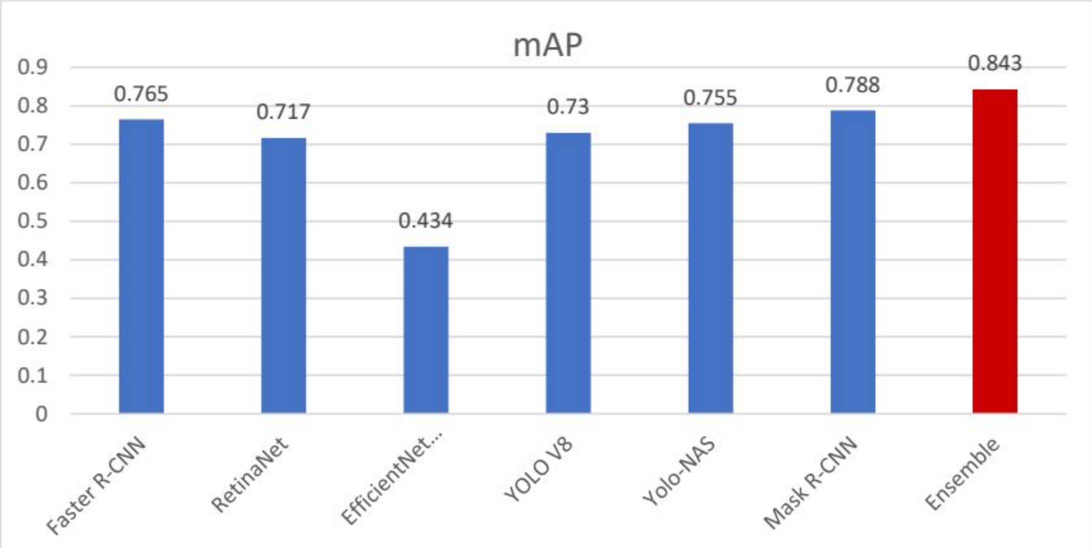


Fig. 5.8 Mean Average Precision (mAP) of Different Models

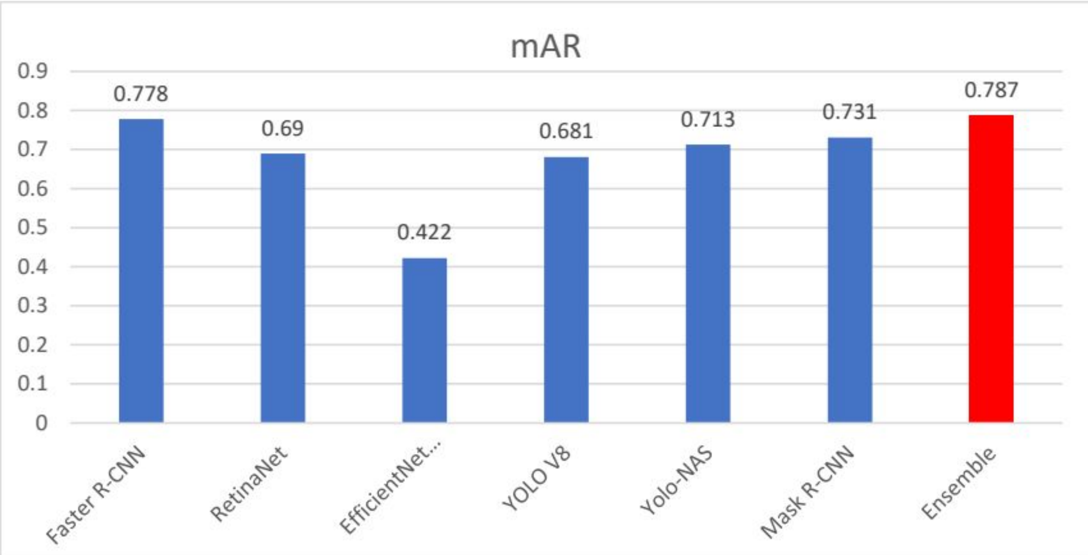


Fig. 5.9 Mean Average Recall (mAR) of Different Models

The Mask R-CNN ensemble model of YOLO-NAS performs really great, obtaining the following highest metrics: mAP of 0.843, mAR of 0.787, and F1 score of 0.814; therefore, the distinguished capacity in handling the nuances of traffic light detection. Since the integrated prediction of these two powerful models enhances the performance of the model, this section will further elaborate more on their predictive accuracies which will help in discussing the possible implications of applying them to design more sophisticated traffic management systems. The objective contribution from the advanced ensemble model goes to reduce congestion and, consequently, improve safety—through improving mechanisms for the prediction of traffic lights—exactly in the scope of the mission to advance ITS with new machine learning solutions.

As seen, the details of performance were given for the model's capability in detecting traffic lights from all classes of traffic signs using precision and recall performance metrics. The table contains an occurrence of different classes of traffic signs, as defined by their name and ClassID, along with the total number of occurrences within the dataset. There are precision values, which are the ratio of the number of positive identifications that were positive to the number of positive identifications that were actually correct; and recall, which is the ratio of the number of actual positives. Employing Equation (4), the number of counts for 'stopleft' is 4,239; Parameter = 0.748, and Recall is 0.843, showing that many true 'stopleft' signs are predicted well, but with some misclassifications. The 'warningleft' sign (ClassID2) has much less total count—only 126 instances—with a higher level of Precision equal to 0.877, but its recall is a bit lower: equal to 0.733. This means the model predicts quite well, but with rather significant numbers, it misses the occurrences of 'warningleft'. The classID 3 traffic sign—go—has the highest number of instances: 15,563, with relatively high values of Precision and Recall. Regarding effective detection, this implies even in such a large volume of data. Such analysis, in detail, helps in understanding the strengths and limitations of the model for detecting and correctly classifying different traffic signs, which is extremely important in ensuring that the system is robust and effective in real-world traffic management scenarios.

5.4 Traffic Accident trend Prediction

This section of the thesis presents a descriptive discussion of results obtained from an innovative ensemble model that combines feedforward neural network (FNN) and long short-term memory (LSTM) network techniques into the prediction for traffic accident occurrences. Integration of such models is currently at the cutting edge of our research on enhancing traffic flow and ensuring safety using intelligent transportation systems based on advanced machine learning technologies. These optimizations are the design strength of the ensemble approach, which is popular for its effective performance power with a diverse set of input feature sets using FNN and also for its effective applicability in sequential data handling and modelling of temporal dependencies using LSTM.

Table 5.6. Performance Comparison of Prediction Techniques

Technique	**MSE**	**RMSE**	**R^2**
LSTM	0.00489319	0.6995137	0.9983709
FNN	0.00976033	0.9879442	0.9967505
Ensemble	0.00172280	0.0415067	0.999426

This performance was further validated intensely with the independently tested validation dataset for ensemble and individual LSTM and FNN models, following two basic statistical metrics: mean-squared error (MSE) and coefficient of determination R^2. These results, therefore, allow certain insight into overall accuracies and efficacies of the models in predicting traffic accidents. For example, the most performing ensemble model had the least MSE of 0.00172280 and RMSE of 0.0415067 with $R^2 = 0.999426$ that was hence close to 1, showing great data fitness, meaning it predicts with very minute error and writes down virtually all variability in the accident data, thus very reliable and accurate for prediction.

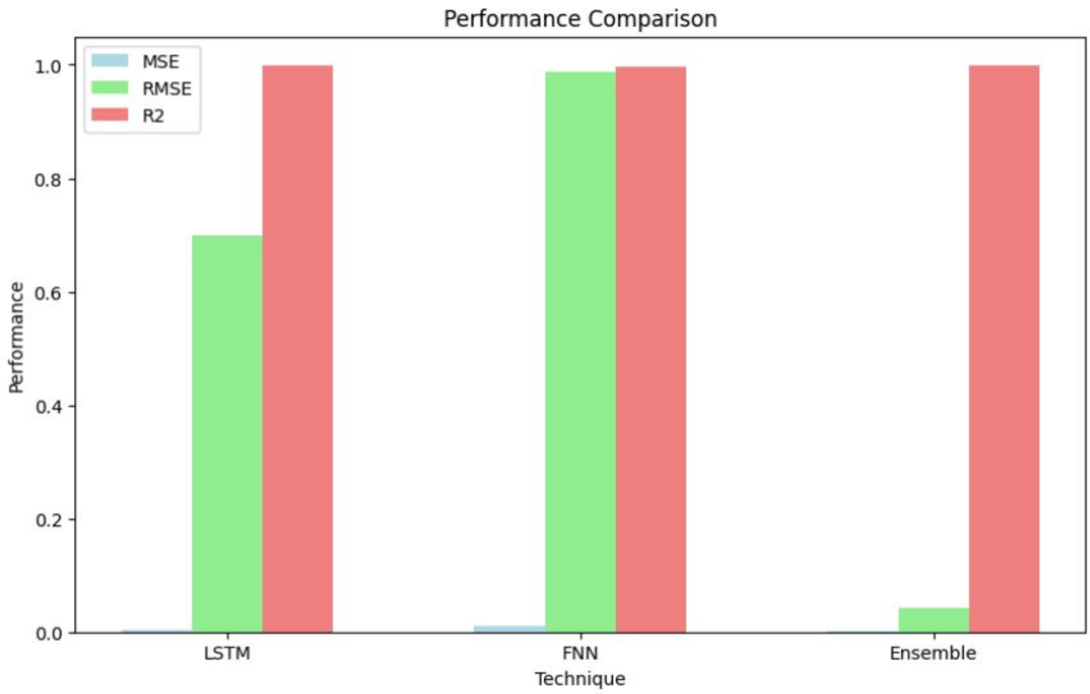


Fig. 5.10. Performance Comparison of Techniques

CHAPTER 6

CONCLUSION, FUTURE SCOPE AND SOCIAL IMPACT

In this dissertation, we have systematically looked over the application and use of advanced machine learning techniques for enhancing the flow and safety of traffic in the domain of Intelligent Transportation Systems. We did show through detailed research in multiple research papers that machine learning can greatly increase capabilities regarding dealing with and predicting traffic circumstances effectively. The deployment of machine learning models, from ensemble methods to technologies such as YOLOv8 with Detectron2 in traffic sign detection and Feedforward Neural Networks with Long Short-Term Memory networks in accident prediction, is central to this research. These models have had high capabilities compared to the models used previously when increasing the precision to detect and predict different elements, directly impacting both safety and flow.

Machine learning models, such as SVR, Bi-LSTM and attention-based Conv-LSTM, have shown an enormous traffic forecasting improvement. These technologies have applied in making exact predictions of traffic densities and patterns, hence assisting in more proactive strategies of managing traffic. Especially the ensemble model of YOLOv8 combined with Detectron2 acquired the all-time high-rate accuracy benchmark for traffic sign recognition, which underpins the safety mechanisms required in autonomous driving and real-time traffic management.

Additionally, a successful implementation combining the Yolo-NAS and Mask R-CNN models for traffic light prediction has proven to work better than others in the prediction test, reducing congestion on the roads by far, thereby bringing efficiency into the navigation procedure across an urban environment. A similar approach, ensembling FNN and LSTM in traffic accident prediction, has offered tracks for effective preemptive actions regarding hot spot accidents, in which action could be put in place to ensure safety for road users and maximize traffic operations' efficiency.

To sum up, the conducted research has reconfirmed those advanced applications of machine learning models within ITS make significant advances in managing and protecting traffic environments in urban centers. There are improvements in the accuracy of traffic predictions, and improvements now give further scope for developing smarter and more sustainable urban transportation networks. This paves the way for the integration of such technologies into ITS, and a promising way forward—particularly in the context of extending these models to cover other predictive needs and scenarios. There is an increasing need to enhance safety in line with the exponential increase in urbanization, as well as improve transport operation through intelligent machine learning solutions. The thesis further ads to this evolving landscape and provides grounds for future innovations in technology, or whatever changes the future may bring, in transportation technology and management.

6.1. Future Scope and Social Impact

There is boundless scope for growth and the application of machine learning within ITS. This offers opportunities for considerable societal gain while future research can be made much better by the new models, taking much other type of data input, real-time social media feeds, and much broader environmental factors, enhancing further the predictive accuracies and response times. The use of edge computing integrated with data analytics and machine learning models could help to make data processing more decentralized, help in the increased responsiveness of ITS, and lessen the load on the central servers. This will most essentially help in large urban areas where traffic decisions are time-based.

An alternative promising direction is that of unsupervised and reinforcement learning algorithms for the traffic management problem. These, in a way, learn from flows of traffic at each moment and change optimization strategies over time, but without predefined labels. This no doubt would lead to much more resilient and adaptive traffic systems than those that could cope with unexpected conditions or trends in travel patterns with human intervention.

Impacting society, the better traffic management by ITS directly relates to the decrease in vehicle emissions toward environmental sustainability. This can also substantially save time that a commuter spends in traffic through proper predictions and traffic controls, hence productivity increases and stress decreases. Additionally, the safety improvements garnered from accurate traffic prediction and corresponding management could reduce traffic accidents, injuries, and fatalities, thereby having profound consequences on public health and safety.

Further, successful advanced ITS implantation could be seen as the most crucial cornerstone for public trust in autonomous technologies worldwide and the opening of paths to wide acceptance and integrations of autonomous vehicles. In other words, upgrading ITS with the help of machine learning improves transportation efficiency and safety and fosters social advancement towards more innovative, sustainable urban living environments.

With the aforementioned background information in mind, the thesis of this paper is that machine learning is applied to improve ITS and the general implications derived from such advancements on society. It is a path of continuous innovation, where the point of convergence among technology, urban planning, and the needs of society could lead forward into the future full of sustainable and efficient prospects.

REFERENCES

[1]. Meena, G., Sharma, D. and Mahrishi, M. (2020) 'Traffic prediction for Intelligent Transportation System using machine learning', *2020 3rd International Conference on Emerging Technologies in Computer Engineering: Machine Learning and Internet of Things (ICETCE)* [Preprint]. doi:10.1109/icetce48199.2020.9091758.

[2]. Javed, M.A., Ngo, D.T. and Khan, J.Y. (2015) 'Distributed spatial reuse distance control for basic safety messages in SDMA-based VANETs', *Vehicular Communications, 2(1),* pp. 27–35. doi:10.1016/j.vehcom.2014.12.001.

[3]. Javed, M., Ben Hamida, E. and Znaidi, W. (2016) 'Security in Intelligent Transport Systems for smart cities: From theory to practice', *Sensors, 16(6), p. 879.* doi:10.3390/s16060879.

[4]. Guerrero-ibanez, J.A., Zeadally, S. and Contreras-Castillo, J. (2015) 'Integration challenges of intelligent transportation systems with connected vehicle, cloud computing, and internet of things technologies', *IEEE Wireless Communications, 22(6),* pp. 122–128. doi:10.1109/mwc.2015.7368833.

[5]. H. Gao, W. Huang, and X. Yang, "Applying probabilistic model checking to path planning in an intelligent transportation system using mobility trajectories and their statistical data," *Intelligent Automation and Soft Computing, 2019.* doi:10.31209/2019.100000110

[6]. F. Ogwueleka, S. Misra, T. Ogwueleka, and L. Fernandez-Sanz, "An Artificial Neural network model for road accident prediction: A case study of a developing country," *Acta Polytechnica Hungarica,* vol. 11, no. 5, Jul. 2014, doi: 10.12700/aph.11.05.2014.05.11.

[7]. U. Bhardwaj, A. P. Teixeira, and C. G. Soares, "Casualty analysis methodology and taxonomy for FPSO accident analysis," *Reliability Engineering & Systems Safety,* vol. 218, p. 108169, Feb. 2022, doi: 10.1016/j.ress.2021.108169.

[8]. G. Bello-Orgaz, J. J. Jung, and D. Camacho, "Social big data: Recent achievements and new challenges," *Information Fusion,* vol. 28, pp. 45–59, Mar. 2016, doi: 10.1016/j.inffus.2015.08.005.

[9]. J. Cao, C. Song, S. Peng, F. Xiao, and S. Song, "Improved traffic sign detection and recognition algorithm for intelligent vehicles," *Sensors,* vol. 19, no. 18, p. 4021, Sep. 2019, doi: 10.3390/s19184021.

[10]. X. Qin and J. Han, "Variable selection issues in Tree-Based regression models," *Transportation Research Record,* vol. 2061, no. 1, pp. 30–38, Jan. 2008, doi: 10.3141/2061-04.

[11]. A. L. Samuel, "Some studies in machine learning using the game of checkers," *IBM Journal of Research and Development,* vol. 3, no. 3, pp. 210–229, Jul. 1959, doi: 10.1147/rd.33.0210.

[12]. Q. Ling, "Machine learning algorithms review," *Applied and Computational Engineering, vol. 4, no. 1*, pp. 91–98, Jun. 2023, doi: 10.54254/2755-2721/4/20230355.

[13]. S. Tanwar, S. Tyagi, and S. Kumar, "The role of internet of things and smart grid for the development of a smart city," *in Lecture notes in networks and systems, 2017*, pp. 23–33. doi: 10.1007/978-981-10-5523-2_3.

[14]. M.-Y. Fu and Y.-S. Huang, "A survey of traffic sign recognition," *International Conference on Wavelet Analysis and Pattern Recognition, Jul. 2010*, doi: 10.1109/icwapr.2010.5576425.

[15]. M. Abdel-Aty, J. Keller, and P. Brady, "Analysis of types of crashes at signalized intersections by using complete crash data and Tree-Based regression," *Transportation Research Record*, Jan. 2005, doi: 10.3141/1908-05.

[16]. Y. Feng, D. Kong, P. Wei, H. Sun, and N. Zheng, "A Benchmark Dataset and Multi-Scale Attention Network for Semantic Traffic Light Detection," *IEEE Intelligent Transportation Systems Conference, Oct. 2019*, doi: 10.1109/itsc45078.2019.9086430.

[17]. H. Jayarathne, T. Samarakoon, H. Koralege, A. Divisekara, R. Rodrigo, and P. Jayasekara, "DualCam: A Novel Benchmark Dataset for Fine-Grained Real-Time Traffic Light Detection," *arXiv Preprint, Dec. 2023*, doi: 10.1109/icmla58977.2023.00270.

[18]. A. Theofilatos, "Incorporating real-time traffic and weather data to explore road accident likelihood and severity in urban arterials," *Journal of Safety Research,* vol. 61, pp. 9–21, Jun. 2017, doi: 10.1016/j.jsr.2017.02.003.

[19]. M. M. Chen and M. C. Chen, "Modeling Road Accident Severity with Comparisons of Logistic Regression, Decision Tree and Random Forest," *Information,* vol. 11, no. 5, p. 270, May 2020, doi: 10.3390/info11050270.

[20]. K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Jun. 2016*, doi: 10.1109/cvpr.2016.90.

[21]. J. Rapp, J. Tachella, Y. Altmann, S. McLaughlin, and V. K. Goyal, "Advances in Single-Photon LIDAR for autonomous vehicles: working principles, challenges, and recent advances," *IEEE Signal Processing Magazine,* vol. 37, no. 4, pp. 62–71, Jul. 2020, doi: 10.1109/msp.2020.2983772.

[22]. M. Sokolova and G. Lapalme, "A systematic analysis of performance measures for classification tasks," *Information Processing & Management,* vol. 45, no. 4, pp. 427–437, Jul. 2009, doi: 10.1016/j.ipm.2009.03.002.

[23]. Z. Ennahhal, I. Berrada, and K. Fardousse, "Real Time Traffic Light Detection and Classification using Deep Learning," *International Conference on Wireless Networks and Mobile Communications (WINCOM), Oct. 2019*, doi: 10.1109/wincom47513.2019.8942446.

[24]. J. R. V. Rivero, T. Gerbich, B. Buschardt, and J. Chen, "Data Augmentation of Automotive LIDAR Point Clouds under Adverse Weather Situations," S*ensors,* vol. 21, *no. 13*, p. 4503, Jun. 2021, doi: 10.3390/s21134503.

[25]. C. Liu et al., "City-Scale Multi-Camera Vehicle Tracking Guided by Crossroad Zones," *IEEE/CVF Conference on Computer Vision and Pattern Recognition, Jun. 2021*, doi: 10.1109/cvprw53098.2021.00466.

[26]. H. Zhao, W. Zhou, X. Hou, and H. Zhu, "Double attention for Multi-Label image classification," *IEEE Access,* vol. 8, *pp. 225539–225550, Jan. 2020*, doi: 10.1109/access.2020.3044446.

[27]. H. Lee, J. Sa, Y. Chung, D. Park, and H. Kim, "Deep Learning-based Overlapping-PIg separation by balancing accuracy and execution time," *Computer Science Research Notes, Jan. 2019*, doi: 10.24132/csrn.2019.2901.1.3.

[28]. R. K. C. Chan, J. M.-Y. Lim, and R. Parthiban, "A neural network approach for traffic prediction and routing with missing data imputation for intelligent transportation system," *Expert Systems With Applications,* vol. 171*,* p. 114573, Jun. 2021, doi: 10.1016/j.eswa.2021.114573.

[29]. C. Li and P. Xu, "Application on traffic flow prediction of machine learning in intelligent transportation," *Neural Computing & Applications,* vol. 33, no. 2, pp. 613–624, Jun. 2020, doi: 10.1007/s00521-020-05002-6.

[30]. C. Chen, B. Liu, S. Wan, P. Qiao, and Q. Pei, "An edge traffic flow detection scheme based on deep learning in an intelligent transportation system," I*EEE Transactions on Intelligent Transportation Systems,* vol. 22, no. 3, pp. 1840–1852, Mar. 2021, doi: 10.1109/tits.2020.3025687.

[31]. X. Wang, J. Liu, T. Qiu, C. Mu, C. Chen, and P. Zhou, "A Real-Time collision prediction mechanism with deep learning for intelligent transportation system," *IEEE Transactions on Vehicular Technology,* vol. 69, no. 9, pp. 9497–9508, Sep. 2020, doi: 10.1109/tvt.2020.3003933.

[32]. F. Zhou, Q. Yang, T. Zhong, D. Chen, and N. Zhang, "Variational Graph Neural networks for road traffic prediction in intelligent transportation systems," *IEEE Transactions on Industrial Informatics,* vol. 17, no. 4, pp. 2802–2812, Apr. 2021, doi: 10.1109/tii.2020.3009280.

[33]. N. Kumar, S. S. Rahman, and N. Dhakad, "Fuzzy inference enabled deep reinforcement Learning-Based traffic Light control for intelligent transportation system," *IEEE Transactions on Intelligent Transportation Systems,* vol. 22, no. 8, pp. 4919–4928, Aug. 2021, doi: 10.1109/tits.2020.2984033.

[34]. S. Guo, Y. Lin, N. Feng, C. Song, and H. Wan, "Attention based Spatial-Temporal Graph convolutional networks for traffic flow forecasting," *Proceedings of the ... AAAI Conference on Artificial Intelligence,* vol. 33, no. 01, pp. 922–929, Jul. 2019, doi: 10.1609/aaai.v33i01.3301922.

[35]. L. Li, X. Qu, J. Zhang, Y. Wang, and B. Ran, "Traffic speed prediction for intelligent transportation system based on a deep feature fusion model," *Journal of Intelligent Transportation Systems,* vol. 23, no. 6, pp. 605–616, Mar. 2019, doi: 10.1080/15472450.2019.1583965.

[36]. A. Ferdowsi, U. Challita, and W. Saad, "Deep learning for reliable mobile edge analytics in intelligent transportation Systems: an Overview," *IEEE Vehicular Technology Magazine,* vol. 14, no. 1, pp. 62–70, Mar. 2019, doi: 10.1109/mvt.2018.2883777.

[37]. A. Ashwini, K. E. Purushothaman, B. P. Prathaban, M. Jenath, and R. Prasanna, "Automatic Traffic Sign Board Detection from Camera Images Using Deep learning and Binarization Search Algorithm," *International Conference on Recent Advances in Electrical, Electronics, Ubiquitous Communication, and Computational Intelligence (RAEEUCCI), Apr. 2023*, doi: 10.1109/raeeucci57140.2023.10134376.

[38]. R. S. Prashanth and T. Devi, "An Efficient Traffic Sign Board Detection Approach using Convolutional Neural Network in Comparison with Radial Basis Function with Improved Accuracy," *2022 14th International Conference on Mathematics, Actuarial Science, Computer Science and Statistics (MACS), Nov. 2022*, doi: 10.1109/macs56771.2022.10023092.

[39]. Y. Zhang, S. Zhang, D. Xin, and D. Chen, "A small target pedestrian detection model based on autonomous driving," *Journal of Advanced Transportation,* vol. 2023, pp. 1–15, Feb. 2023, doi: 10.1155/2023/5349965.

[40]. C. Zhao and W. Zheng, "Fast Traffic Sign Recognition Algorithm Based on Multi-scale Convolutional Neural Network," *Eighth International Conference on Advanced Cloud and Big Data (CBD), Dec. 2020*, doi: 10.1109/cbd51900.2020.00031.

[41]. D. Temel, M.-H. Chen, and G. AlRegib, "Traffic Sign Detection Under Challenging Conditions: A Deeper Look into Performance Variations and Spectral Characteristics," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 9, pp. 3663–3673, Sep. 2020, doi: 10.1109/tits.2019.2931429.

[42]. C. Krittanawong et al., “Deep learning for cardiovascular medicine: a practical primer,” *European Heart Journal,* vol. 40, no. 25, pp. 2058–2073, Feb. 2019, doi: 10.1093/eurheartj/ehz056.

[43]. L. Jiao et al., “A survey of Deep Learning-Based Object Detection,” *IEEE Access, vol. 7*, pp. 128837–128868, Jan. 2019, doi: 10.1109/access.2019.2939201.

[44]. N. Triki, M. Karray, and M. Ksantini, “A Real-Time traffic sign recognition method using a new Attention-Based Deep Convolutional neural network for smart vehicles,” *Applied Sciences, vol. 13, no. 8*, p. 4793, Apr. 2023, doi: 10.3390/app13084793.

[45]. J. Dai, Y. Li, K. He, and J. Sun, “R-FCN: object detection via region-based fully convolutional networks,” *arXiv (Cornell University),* vol. 29, pp. 379–387, May 2016, [Online]. Available: https://arxiv.org/pdf/1605.06409

[46]. M. Atif, T. Zoppi, M. Gharib, and A. Bondavalli, “Towards Enhancing Traffic Sign Recognition through Sliding Windows,” *Sensors,* vol. 22, no. 7, p. 2683, Mar. 2022, doi: 10.3390/s22072683.

[47]. Y. M. Elbon, M. M. Ghantous, and Y. S. Melek, “Traffic Light Recognition with Prior Maps,” *International Conference on Signal-Image Technology & Internet-Based Systems (SITIS), Oct. 2022,* doi: 10.1109/sitis57111.2022.00026.

[48]. M. B. Jensen, K. Nasrollahi, and T. B. Moeslund, “Evaluating State-of-the-Art Object Detector on Challenging Traffic Light Data,” *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, Jul. 2017*, doi: 10.1109/cvprw.2017.122.

[49]. C. Lyu, X. Fan, Z. Qiu, J. Chen, J. Lin, and C. Dong, “Efficientdet Based Visial Perception for Autonomous Driving,” *8th International Conference on Cloud Computing and Big Data Analytics (ICCCBDA), Apr. 2023*, doi: 10.1109/icccbda56900.2023.10154715.

[50]. E. Guney, C. Bayilmis, and B. Cakan, “An implementation of Real-Time traffic signs and road objects detection based on mobile GPU platforms,” *IEEE Access,* vol. 10, pp. 86191–86203, Jan. 2022, doi: 10.1109/access.2022.3198954.

[51]. Z. Ouyang, J. Niu, Y. Liu, and M. Guizani, “Deep CNN-Based Real-Time Traffic Light Detector for Self-Driving vehicles,” *IEEE Transactions on Mobile Computing,* vol. 19, *no. 2*, pp. 300–313, Feb. 2020, doi: 10.1109/tmc.2019.2892451.

[52]. S. Yan, X. Liu, W. Qian, and Q. Chen, “An End-to-End traffic light detection algorithm based on deep learning,” 2*021 International Conference on Security, Pattern Analysis, and Cybernetics (SPAC), Jun. 2021*, doi: 10.1109/spac53836.2021.9539934.

[53]. X. Li, H. Ma, X. Wang, and X. Zhang, “Traffic light recognition for complex scene with fusion detections,” I*EEE Transactions on Intelligent Transportation Systems,* vol. 19, *no. 1,* pp. 199–208, Jan. 2018, doi: 10.1109/tits.2017.2749971.

[54]. Y. Yan, C. Deng, J. Ma, Y. Wang, and Y. Li, “A traffic sign recognition method under complex illumination conditions,” *IEEE Access,* vol. 11, pp. 39185–39196, Jan. 2023, doi: 10.1109/access.2023.3266825.

[55]. P. Liu and T. Li, “Traffic light detection based on depth improved YOLOV5,” *8th International Conference on Intelligent Computing and Signal Processing (ICSP), Feb. 2023,* doi: 10.1109/nnice58320.2023.10105786.

[56]. Zarei, Mohammad, Bruce Hellinga, and Pedram Izadpanah. "CGAN-EB: A non-parametric empirical Bayes method for crash frequency modeling using conditional generative adversarial networks as safety performance functions." *International Journal of Transportation Science and Technology 12, no. 3 (2023*): 753-764.

[57]. Amorim, Brunna de Sousa Pereira, Anderson Almeida Firmino, Cláudio de Souza Baptista, Geraldo Braz Júnior, Anselmo Cardoso de Paiva, and Francisco Edeverton de Almeida Júnior. "A Machine Learning Approach for Classifying Road Accident Hotspots." I*SPRS International Journal of Geo-Information 12, no. 6 (2023)*: 227.

[58]. Saravanarajan, Vani Suthamathi, Rung-Ching Chen, Christine Dewi, Long-Sheng Chen, and Lata Ganesan. "Car crash detection using ensemble deep learning." *Multimedia Tools and Applications (2023)*: 1-19.

[59]. Gutierrez-Osorio C., González F. A., Pedraza C. A.: Deep Learning Ensemble Model for the Prediction of Traffic Accidents Using Social Media Data. Computers 11(9), 2022, 126.

[60]. Comi, Antonio, Antonio Polimeni, and Chiara Balsamo. "Road accident analysis with data mining approach: evidence from Rome." *Transportation research procedia 62 (2022)*: 798-805.

[61]. Zheng, Haifeng, Feng Lin, Xinxin Feng, and Youjia Chen. "A hybrid deep learning model with attention-based conv-LSTM networks for short-term traffic flow prediction." *IEEE Transactions on Intelligent Transportation Systems 22, no. 11 (2020)*: 6910-6920.

[62]. Chen, Hengrui, Hong Chen, Ruiyu Zhou, Zhizhen Liu, and Xiaoke Sun. "Exploring the mechanism of crashes with autonomous vehicles using machine learning." *Mathematical problems in engineering 2021 (2021)*: 1-10.

[63]. Choi, Jae Gyeong, Chan Woo Kong, Gyeongho Kim, and Sunghoon Lim. "Car crash detection using ensemble deep learning and multimodal data from dashboard cameras." *Expert Systems with Applications 183 (2021)*: 115400.

[64]. Rahman, Md Sharikur, Mohamed Abdel-Aty, Samiul Hasan, and Qing Cai. "Applying machine learning approaches to analyze the vulnerable road-users' crashes at statewide traffic analysis zones." *Journal of safety research 70 (2019)*: 275-288.

[65]. G. Meena, D. Sharma, and M. Mahrishi, "Traffic Prediction for Intelligent Transportation System using Machine Learning," *3rd International Conference on Emerging Technologies in Computer Engineering: Machine Learning and Internet of Things (ICETCE), Feb. 2020*, doi: 10.1109/icetce48199.2020.9091758.

[66]. J. Yang, J. Li, L. Wei, L. Gao, and F. Mao, "Spatiotemporal DeepWalk Gated Recurrent Neural Network: a deep learning framework for traffic learning and forecasting," *Journal of Advanced Transportation,* vol. 2022, pp. 1–11, Apr. 2022, doi: 10.1155/2022/4260244.

[67]. Z. Su, T. Liu, X. Hao, and X. Hu, "Spatial-temporal graph convolutional networks for traffic flow prediction considering multiple traffic parameters," *the Journal of Supercomputing/Journal of Supercomputing,* vol. 79*, no. 16*, pp. 18293–18312, May 2023, doi: 10.1007/s11227-023-05383-0.

[68]. J. Mishra and S. Goyal, "An effective automatic traffic sign classification and recognition deep convolutional networks," *Multimedia Tools and Applications,* vol. 81, no. 13, pp. 18915–18934, Mar. 2022, doi: 10.1007/s11042-022-12531-w.

[69]. R. K. Megalingam, K. Thanigundala, S. R. Musani, H. Nidamanuru, and L. Gadde, "Indian traffic sign detection and recognition using deep learning," *International Journal of Transportation Science and Technology,* vol. 12, no. 3, pp. 683–699, Sep. 2023, doi: 10.1016/j.ijtst.2022.06.002.

[70]. L. Yu, X. Xia, and K. Zhou, "Traffic sign detection based on visual co-saliency in complex scenes," *Applied Intelligence,* vol. 49, no. 2, pp. 764–790, Sep. 2018, doi: 10.1007/s10489-018-1298-8.

[71]. M. A. Khan, H. Park, and J. Chae, "A Lightweight Convolutional Neural network (CNN) architecture for traffic sign recognition in urban road networks," *Electronics,* vol. 12, no. 8, p. 1802, Apr. 2023, doi: 10.3390/electronics12081802.

[72]. K. Islam and R. Raj, "Real-Time (Vision-Based) road sign recognition using an artificial neural network," *Sensors, vol. 17, no. 4,* p. 853, Apr. 2017, doi: 10.3390/s17040853.

[73]. F. Ogwueleka, S. Misra, T. Ogwueleka, and L. Fernandez-Sanz, "An Artificial Neural network model for road accident prediction: A case study of a developing country,"

Acta Polytechnica Hungarica, vol. 11, no. 5, *Jul. 2014*, doi: 10.12700/aph.11.05.2014.05.11.

[74]. A. Perini, A. Susi, and P. Avesani, "A machine learning approach to software requirements prioritization," *IEEE Transactions on Software Engineering,* vol. 39, no. 4, pp. 445–461, Apr. 2013, doi: 10.1109/tse.2012.52.

[75]. C. Shorten and T. M. Khoshgoftaar, "A survey on Image Data Augmentation for Deep Learning," *Journal of Big Data,* vol. 6, no. 1, *Jul. 2019*, doi: 10.1186/s40537-019-0197-0.

[76]. A. A. Akimov, Valitov, and A. I. Kubryak, "DATA PREPROCESSING FOR MACHINE LEARNING," *Naučnoe Obozrenie. Tehničeskie Nauki, no. №2 2022*, pp. 26–31, Jan. 2022, doi: 10.17513/srts.1391.

[77]. T. Chai and R. R. Draxler, "Root mean square error (RMSE) or mean absolute error (MAE)? – Arguments against avoiding RMSE in the literature," *Geoscientific Model Development,* vol. 7, no. 3, pp. 1247–1250, Jun. 2014, doi: 10.5194/gmd-7-1247-2014.

[78]. J. Qi, J. Du, S. M. Siniscalchi, X. Ma, and C.-H. Lee, "On mean absolute error for deep neural network based Vector-to-Vector regression," I*EEE Signal Processing Letters,* vol. 27, pp. 1485–1489, Jan. 2020, doi: 10.1109/lsp.2020.3016837.

[79]. Y.-J. Lee and O. Min, "Comparative analysis of machine learning algorithms to urban traffic prediction," I*nternational Conference on Information and Communication Technology Convergence (ICTC), Oct. 2017*, doi: 10.1109/ictc.2017.8190846.

[80]. D. Sisodia and D. S. Sisodia, "Prediction of Diabetes using Classification Algorithms," *Procedia Computer Science,* vol. 132, pp. 1578–1585, Jan. 2018, doi: 10.1016/j.procs.2018.05.122.

[81]. A. J. Smola and B. Schölkopf, "A tutorial on support vector regression," Statistics and *Computing,* vol. 14, no. 3, pp. 199–222, Aug. 2004, doi: 10.1023/b:stco.0000035301.49549.88.

[82]. K. Chhantyal, H. Viumdal, and S. Mylvaganam, "Soft sensing of Non-Newtonian fluid flow in open venturi channel using an array of Ultrasonic Level Sensors—AI models and their validations," *Sensors,* vol. 17, no. 11, p. 2458, Oct. 2017, doi: 10.3390/s17112458.

[83]. J. Terven, D.-M. Córdova-Esparza, and J.-A. Romero-González, "A comprehensive review of YOLO architectures in computer vision: from YOLOV1 to YOLOV8 and YOLO-NAS," *Machine Learning and Knowledge Extraction,* vol. 5, no. 4, pp. 1680–1716, Nov. 2023, doi: 10.3390/make5040083.

[84]. M. S. Asyraf, I. S. Isa, M. I. F. Marzuki, S. N. Sulaiman, and C. C. Hung, "CNN-based YOLOV3 comparison for underwater object detection," J*ournal of Electrical and Electronic Systems Research,* vol. 18, no. APR2021, pp. 30–37, Apr. 2021, doi: 10.24191/jeesr.v18i1.005.

[85]. R.-Y. Ju and W. Cai, "Fracture detection in pediatric wrist trauma X-ray images using YOLOv8 algorithm," *Scientific Reports,* vol. 13, no. 1, *Nov. 2023*, doi: 10.1038/s41598-023-47460-7.

[86]. A. V. S. Abhishek and S. Kotni, "Detectron2 Object Detection & Manipulating Images using Cartoonization," *International Journal of Engineering Research and Technology,* vol. 10, no. 8*, Aug. 2021*.

[87]. M. K. Sarker et al., "A means of assessing Deep Learning-Based detection of ICOS protein expression in colon cancer," *Cancers,* vol. 13, no. 15, p. 3825, Jul. 2021, doi: 10.3390/cancers13153825.

[88]. T. G. Dietterich, "Ensemble methods in machine learning," i*n Lecture notes in computer science, 2000*, pp. 1–15. doi: 10.1007/3-540-45014-9_1.

[89]. N. D. Hendrawan and R. Kolandaisamy, "A comparative study of YOLOV8 and YOLO - NAS performance in human Detection image," *Jurnal Teknologi Dan Manajemen*

Informatika/Jurnal Teknologi Dan Manajemen Informatika, vol. 9, no. 2, pp. 191–201, Jan. 2023, doi: 10.26905/jtmi.v9i2.12192.

[90]. А. Маратулы and Е. А. Абибуллаев, "PERFORMANCE STUDY AND COMPARATIVE ANALYSIS OF YOLO-NAS AND PREVIOUS VERSIONS OF YOLO," *International Journal of Information and Communication Technologies,* vol. 5, no. 1(17), pp. 71–83, Mar. 2024, doi: 10.54309/ijict.2024.17.1.006.

[91]. S. Hu, L. Su, H. Liu, H. Wang, and T. F. Abdelzaher, "SmartRoad," *ACM Transactions on Sensor Networks,* vol. 11, no. 4, pp. 1–27, Jul. 2015, doi: 10.1145/2770876.

[92]. K. He, G. Gkioxari, P. Dollar, and R. Girshick, "Mask R-CNN," *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 42, no. 2, pp. 386–397, Feb. 2020, doi: 10.1109/tpami.2018.2844175.

[93]. W. Zhao, Y. Gao, T. Ji, X. Wan, F. Ye, and G. Bai, "Deep Temporal convolutional networks for Short-Term Traffic Flow Forecasting," *IEEE Access,* vol. 7, pp. 114496–114507, Jan. 2019, doi: 10.1109/access.2019.2935504.

[94]. S. Podder, S. Bhattacharjee, and A. Roy, "An efficient method of detection of COVID-19 using Mask R-CNN on chest X-Ray images," *AIMS Biophysics,* vol. 8, no. 3, pp. 281–290, Jan. 2021, doi: 10.3934/biophy.2021022.

[95]. Z.-H. Zhou, Ensemble Methods: Foundations and Algorithms. 2012. [Online]. *Available:* http://dx.doi.org/10.1201/b12207

[96]. Jamal, Arshad, Muhammad Zahid, Muhammad Tauhidur Rahman, Hassan M. Al-Ahmadi, Meshal Almoshaogeh, Danish Farooq, and Mahmood Ahmad. "Injury severity prediction of traffic crashes with ensemble machine learning techniques: A comparative study." I*nternational journal of injury control and safety promotion 28, no. 4 (2021*): 408-427.

[97]. G. Bebis and M. Georgiopoulos, "Feed-forward neural networks," *IEEE Potentials,* vol. 13, no. 4, pp. 27–31, Oct. 1994, doi: 10.1109/45.329294.

[98]. D. Svozil, V. Kvasnicka, and J. Pospichal, "Introduction to multi-layer feed-forward neural networks," *Chemometrics and Intelligent Laboratory Systems,* vol. 39, no. 1, pp. 43–62, Nov. 1997, doi: 10.1016/s0169-7439(97)00061-0.

[99]. S. J. S. Hakim, J. Noorzaei, M. S. Jaafar, M. Jameel, and M. Mohammadhassani, "Application of artificial neural networks to predict compressive strength of high strength concrete," *International Journal of the Physical Sciences*, vol. 6, no. 5, pp. 975–981, Mar. 2011, doi: 10.5897/ijps11.023.

[100]. S. Hochreiter and J. Schmidhuber, "Long Short-Term memory," *Neural Computation,* vol. 9, no. 8, pp. 1735–1780, Nov. 1997, doi: 10.1162/neco.1997.9.8.1735.

[101]. Cura, Aslıhan, Haluk Küçük, Erdem Ergen, and İsmail Burak Öksüzoğlu. "Driver profiling using long short term memory (LSTM) and convolutional neural network (CNN) methods." I*EEE Transactions on Intelligent Transportation Systems 22, no. 10 (2020)*: 6572-6582.

[102]. O. Surakhi et al., "Time-Lag selection for Time-Series forecasting using neural network and heuristic algorithm," *Electronics,* vol. 10, no. 20, p. 2518, Oct. 2021, doi: 10.3390/electronics10202518.

[103]. R. Ghaemi, Md. N. Sulaiman, H. Ibrahim, and N. Mustapha, "A survey: Clustering Ensembles Techniques," *World Academy of Science, Engineering and Technology, International Journal of Computer, Electrical, Automation, Control and Information Engineering,* vol. 3, no. 2, pp. 365–374, Feb. 2009.

LIST OF PUBLICATIONS

1. *Abhilasha Sharma, Prabhat Ranjan "Traffic Prediction Model Using Machine Learning in Intelligent Transportation Systems"*. The paper has been **Accepted** as well as **Published** at the 2023 ICCPCT. Indexed by **Scopus**. Paper Id: 605

Acceptance Notification- ICCPCT 2023 ICCPCT ×

ICCPCT 2023 <iccpct@gmail.com>
to bcc: me
Tue, May 23, 2023, 4:19 PM

Dear Author,

We are pleased to inform you that your paper has been accepted for presentation. Camera ready submission,copyright form submission and view review options were enabled for the selected paper in your CMT author console.

Please submit
1.**Camera ready paper,copyright form via CMT author console** (copyright form is integrated in cmt account)
2.**Camera ready paper,copyright form,registration form,payment proof** to iccpct@gmail.com mentioning CMT submission ID in subject column.

Paper template and registration form available in https://iccpct.in/Downloads.php

Before Creating camera ready paper PDF

- Add the copyright notice to the bottom of the first page of your source document. (copyright notice **979-8-3503-3324-4/23/$ 31.00 ©2023 IEEE**)
- Proofread your source document thoroughly to confirm that it will require no revision.

Creating your PDF eXpress Account (Paper collection site for IEEE Digital Xplore)
Log in to the IEEE PDF eXpress TM site (https://ieee-pdf-express.org/account/login?ReturnUrl=%2F)

Publication Link: https://ieeexplore.ieee.org/document/10245139

Presentation Certificate:


Baselios Mathews II College of Engineering
Lake View, Muthupilakadu, Poruvazhy (P.O.), Sasthamcotta - 690 520
Kollam, Kerala State, India.
www.bmce.ac.in www.iccpct.in

IEEE Kerala Section
IEEE

International Conference on
Circuit Power and Computing Technologies
ICCPCT- 2023

CERTIFICATE

This is to certify that **Mr. Prabhat Ranjan,** M.Tech Student, Software Engineering Department, Delhi Technological University presented a paper on **Traffic Prediction Model Using Machine Learning In Intelligent Transportation System** in the International Conference, organized by the **Baselios Mathews II College of Engineering** held on 10^{th} and 11^{th} of August 2023.

Dr. L. Padma Suresh
Conference Chair
ICCPCT 2023

Rev.Fr.Thomas Varghese
Director, BMCE

Scopus:

Scopus   Search   Sources

1 of 1

Download Print Save to PDF Save to list Create bibliography

Proceedings of the International Conference on Circuit Power and Computing Technologies, ICCPCT 2023 • Pages 1165 - 1173 • 2023 • 2023 International Conference on Circuit Power and Computing Technologies, ICCPCT 2023 • Kollam • 10 August 2023through 11 August 2023 • Code 192821

Document type
Conference Paper
Source type
Conference Proceedings
ISBN
979-835033324-4
DOI
10.1109/ICCPCT58313.2023.10245139
Publisher
Institute of Electrical and Electronics Engineers Inc.
Original language

Traffic Prediction Model Using Machine Learning in Intelligent Transportation Systems

Sharma, Abhilasha ;
Ranjan, Prabhat
Save all to author list

[a] Delhi Technological University, Department of Software Engineering, Delhi, India

2. *Abhilasha Sharma, Prabhat Ranjan "Traffic Sign Board Prediction Using Ensemble Model of YOLOv8 And Detectron2"*. The paper has been **Accepted** as well as **Published** at the 2023 ICAICCIT. Indexed by **Scopus**. Paper Id: 716

Acceptance Notification IEEE ICAICCIT-23 & Registration: Paper ID 716 Inbox ×

Microsoft CMT <email@msr-cmt.org>   Wed, Sep 20, 2023, 12:57 PM
to me, poonamtanwar.fet, aiccit2023

Dear Author,

Greetings from ICAICCIT-23.

On behalf of the ICAICCIT-23 organizing Committee, we are delighted to inform you that the submission of " paper-id 716 " titled " Traffic Sign Board Prediction Using Ensemble Model of YOLOv8 And Detectron2 accepted for presentation and further publication with IEEE at the ICAICCIT-23 subject to incorporate the reviewers and editors comments in your final paper. All accepted papers will be submitted to IEEE for inclusion into conference proceedings to be published on IEEE Xplore Digital Library.

Registration fee details are available @

https://aiccit2023.vercel.app/registration

Payment to be made through NEFT / RTGS in favor of "Manav Rachna International Institute of Research & Studies" payable at Faridabad.
Please keep the printed details of the fee receipt which will be submitted at the time of physical registration at the conference venue.

Publication link: https://ieeexplore.ieee.org/document/10465993

Presentation Certificate:

IEEE MANAV RACHNA ICAICCIT

Manav Rachna International Institute of Research and Studies
(Deemed-to be-University' under Section 3 of the UGC Act 1956)

CERTIFICATE

OF PARTICIPATION

This is to certify that .... *Prabhat Ranjan* .... of

.... *Delhi Technological University, Delhi* ....has successfully presented a paper

entitled .... *Traffic Sign Board Prediction Using Ensemble Model of YOLOv8 And Detectron2* .... in

2023 International Conference on Advances in Computation ,Communication and Information Technology

Technically Sponsored by IEEE Delhi Section (Record No : 60255)

Organised by

Department of Computer Science & Engineering

Manav Rachna International Institute of Research and Studies, Faridabad, India

23rd -24th November 2023

Poonam Tanwar

Dr. Poonam Tanwar	**Dr. Tapas Kumar**	**Dr. Pardeep Kumar**	**Dr. Sanjay Srivastava**
Professor, CSE,SET	*Associate Dean & HOD-CSE(SPL)*	*Pro-Vice Chancellor*	*Vice Chancellor*
Convener	Conference Chair	Patron	Patron

Scopus:

Scopus — Search — Sources

1 of 1

Download — Print — Save to PDF — Save to list — Create bibliography

2023 International Conference on Advances in Computation, Communication and Information Technology, ICAICCIT 2023 • Pages 378 - 384 • 2023 • 2023 International Conference on Advances in Computation, Communication and Information Technology, ICAICCIT 2023 • Faridabad • 23 November 2023through 24 November 2023 • Code 198271

Traffic Sign Board Prediction Using Ensemble Model of YOLOv8 And Detectron2

Document type
Conference Paper
Source type
Conference Proceedings
ISBN
979-835034438-7
DOI
10.1109/ICAICCIT60255.2023.10465993
View more

Sharma, Abhilasha ; Ranjan, Prabhat

Save all to author list

[a] Delhi Technological University, Department of Software Engineering, Delhi, India

3. *Abhilasha Sharma, Prabhat Ranjan "Synergistic Traffic Light Detection and Interpretation via Integrated YOLO-NAS and Mask R-CNN Framework for Autonomous Systems"*. The paper has been **Accepted** at the 2024 ICPEICES. Indexed by **Scopus**. Paper Id: 1571003178

Decision on your paper #1571003178 for 2024 IEEE Third International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES) External Inbox ×

Edas Help <help@edas.info> Tue, Mar 26, 11:55 AM
to me, Abhilasha

Dear Mr. Prabhat Ranjan:

Congratulations - your paper #1571003178 ('Synergistic Traffic Light Detection and Interpretation via Integrated YOLO-NAS and Mask R-CNN Framework for Autonomous Systems') authored by Prabhat Ranjan and Abhilasha Sharma been **accepted** for presentation in 2024 IEEE Third International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES) to be held from 26th to the 28th of April, 2024 at Delhi Technological University, Delhi – India.

Please visit conference website for Final Paper Submission which includes - Registration, Electronic Copyright Form submission, final manuscript preparation and submission. The version of the final paper/ manuscript should be strictly in an applicable IEEE format.

We are looking forward for your benign presence in ICPEICES2024.

Regards

Chairs

Presentation Certificate:

IEEE

IEEE ICPEICES-2024

3rd IEEE INTERNATIONAL CONFERENCE

on

POWER ELECTRONICS, INTELLIGENT CONTROL AND ENERGY SYSTEMS

26th-28th APRIL, 2024

Department of Electrical Engineering, Delhi Technological University

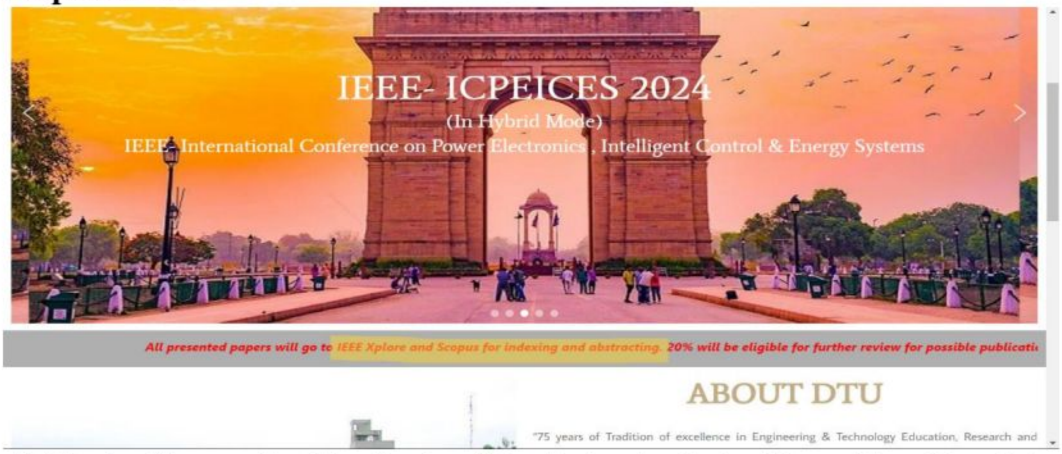
This certificate of Participation/Presentation is awarded to

Dr./Mr./Ms. **Prabhat Ranjan** has attended the conference and presented paper entitled **Synergistic Traffic Light Detection and Interpretation via Integrated YOLO-NAS and Mask R-CNN Framework for Autonomous Systems** authored by **Prabhat Ranjan; Abhilasha Sharma** in the **3rd IEEE International Conference on Power Electronics, Intelligent Control** and Energy Systems held at Delhi Technological University, Delhi, India from 26th - 28th April, 2024.

Prof. Vinod Kumar Yadav
General Chair

Prof. Rachana Garg
General Chair

Scopus Proof:



4. *Abhilasha Sharma, Prabhat Ranjan "Predictive Analysis of Long-Term Trends in Road Accidents and Casualties in India Using Machine Learning: A Focus on Total Fatalities, Killed, and Injured"*. The paper has been **Published** at the 2024 Tuijin Jishu/Journal of Propulsion Technology. Indexed by **Scopus**.

Published Proof:

Hope this mail finds you well.

We would like to congratulate you that your paper titled **Predictive Analysis of Long-Term Trends in Road Accidents and Casualties in India Using Machine Learning: A Focus on Total Fatalities, Killed, and Injured** has been published in the journal **Tuijin Jishu/Journal of Propulsion Technology ISSN: 1001-4055 Vol. 45 No. 2 (2024).**

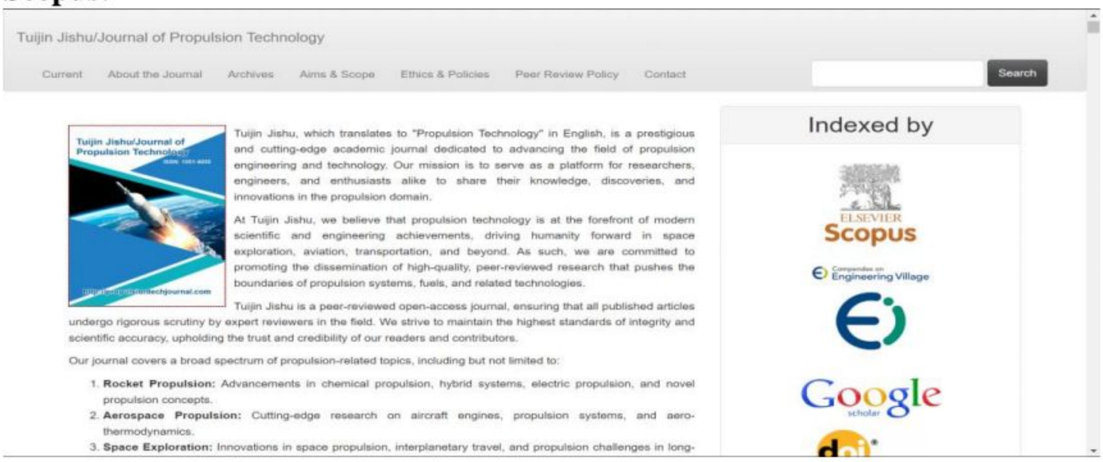
Please go through the following link.

Publication Link: https://propulsiontechjournal.com/index.php/journal/article/view/6401

PDF Link: https://propulsiontechjournal.com/index.php/journal/article/view/6401/4189

Publication Link:https://propulsiontechjournal.com/index.php/journal/article/view/6401

Scopus:



Tuijin Jishu/Journal of Propulsion Technology

Current | About the Journal | Archives | Aims & Scope | Ethics & Policies | Peer Review Policy | Contact | Search

Home / Archives / Vol. 45 No. 02 (2024) / Articles

Predictive Analysis of Long-Term Trends in Road Accidents and Casualties in India Using Machine Learning: A Focus on Total Fatalities, Killed, and Injured

PDF

Keywords:
Road Accidents, Machine Learning, Predictive modelling, Road Safety, Feedforward Neural Networks (FNN) and Long Short-Term Memory (LSTM).

Abhilasha Sharma, Prabhat Ranjan

Abstract

The increasing rates of road crashes and associated fatalities in India have led to immediate concern and action. Despite many efforts, the traditional approaches fail to capture the complicated patterns that exist in road safety dynamics. This paper suggests an innovative method involving machine learning based on historical data analysis and prognosticating models of long-term tendency for road accidents and casualties. Based on an extensive dataset, meticulous data pre-

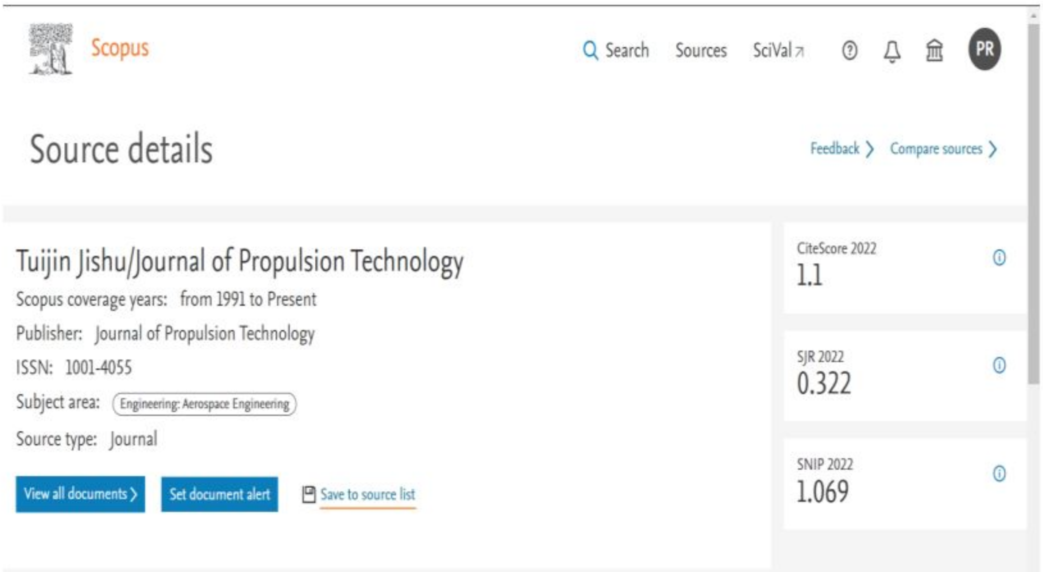
Indexed by

ELSEVIER Scopus

Compendex on Engineering Village

Google scholar

doi



Scopus | Search | Sources | SciVal | PR

Source details

Feedback | Compare sources

Tuijin Jishu/Journal of Propulsion Technology

Scopus coverage years: from 1991 to Present

Publisher: Journal of Propulsion Technology

ISSN: 1001-4055

Subject area: Engineering: Aerospace Engineering

Source type: Journal

View all documents | Set document alert | Save to source list

CiteScore 2022
1.1

SJR 2022
0.322

SNIP 2022
1.069