Evaluating the Efficacy of Deep Learning Architectures in Predicting Traffic Patterns for Smart City Development

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Abstract

Smart city development necessitates the implementation of effective traffic management strategies. In this vein, various deep learning architectures, including VGG16Net, VGG19Net, GoogLeNet, ResNet-50, and AlexNet, are employed to predict diverse traffic patterns extracted from a comprehensive dataset. Evaluating performance metrics such as accuracy, sensitivity, and specificity reveals discernible variations among models, with ResNet-50 and AlexNet demonstrating superior predictive capabilities. Descriptive statistics and statistical analyses, including ANOVA and the Wilcoxon Signed Rank Test, provide nuanced insights into model differences and significance. The findings bear significant implications for urban planners and policymakers transforming cities into intelligent ecosystems, offering valuable insights for informed decision-making in innovative city development. Improved traffic predictions enhance daily commuting experiences and contribute to the informed development of sustainable urban infrastructure, aligning seamlessly with the ongoing evolution of smart cities toward a more connected and efficient future. Notably, AlexNet exhibits a significant accuracy of 0.931780366 in the context of traffic pattern prediction.

Keywords: Smart Cities; Traffic Pattern Prediction; Deep Learning Architectures; VGG16Net; VGG19Net; GoogLeNet; ResNet-50; AlexNet; Urban Development; Traffic Management.

1. Introduction

The contemporary urbanization landscape has witnessed the emergence of smart cities as a visionary model, pledging interconnected, efficient, and sustainable urban habitats. Within this paradigm, the ethical administration of traffic assumes paramount significance, as the unhindered flow of vehicles and pedestrians becomes indispensable to these intelligent urban ecosystems' overall functionality and habitability. In the context of this transformative epoch, this study seeks to substantively contribute

DOI: https://doi.org/10.54216/JAIM.060203
Received: May 16, 2023 Revised: August 22, 2023 Accepted: December 11, 2023

to the discourse on smart city development by delving into the intricate dynamics of traffic patterns. As technology incessantly reshapes urban spaces, the vision of smart cities is propelled by a commitment to harnessing innovation to improve citizens' lives [1]. However, realizing this vision is contingent upon addressing urban challenges, with traffic congestion emerging as a formidable impediment to the seamless operation of smart cities. Acknowledging the pivotal role of effective traffic management in unlocking the full potential of intelligent urbanization, this research embarks on a scholarly journey to explore and comprehend the nuanced intricacies of traffic patterns.

At the heart of this investigation lies the utilization of advanced deep learning architectures, specifically VGG16Net, VGG19Net, GoogLeNet, ResNet-50, and AlexNet, to predict and decipher traffic dynamics within the intricate framework of smart urban ecosystems, as shown in Figure 1. By leveraging the capabilities of these sophisticated models, the aspiration extends beyond mere traffic pattern forecasting to gain profound insights into the underlying factors shaping these patterns. This nuanced understanding proves instrumental in formulating strategies that align with smart city development goals and elevate urban residents' overall quality of life [2-4]. Expounding upon the transformative potential of smart cities, this study transcends the realm of mere traffic prediction; it undertakes a scholarly quest to unearth actionable insights capable of informing the decisions of urban planners, policymakers, and stakeholders. Through a meticulous examination of the performance of diverse deep learning models, this research aspires to establish a scholarly foundation for developing effective and adaptive traffic management strategies tailored to the distinctive challenges posed by smart city environments [5].

Figure 1: Conceptual Framework of a Smart City

As we delve into the intricacies of our paper, three pivotal research questions emerge as the guiding pillars of our investigation:

- How do different deep learning architectures perform in predicting traffic patterns for innovative city development?

DOI: https://doi.org/10.54216/JAIM.060203
Received: May 16, 2023 Revised: August 22, 2023 Accepted: December 11, 2023

- What nuanced variations exist in accuracy, sensitivity, and specificity metrics among the selected deep learning models?
- How can the findings from these predictive models contribute to developing effective traffic management strategies for smart cities?

The subsequent sections of this paper seamlessly follow a structured sequence to comprehensively address the paper questions and contribute meaningfully to the ongoing discourse on innovative city development. The Literature Review section provides an insightful overview of existing literature, contextualizing current research in traffic prediction and creative city development. The Proposed Methodology section meticulously outlines the framework and approach employed in this study to predict traffic patterns using deep learning architectures. Subsequently, the Results section presents empirical findings and analyses, shedding light on the performance nuances of each model. Finally, the Conclusion synthesizes key insights, discusses implications, and suggests avenues for future research in innovative city development and traffic management.

2. Literature Review

Traffic congestion and road safety challenges demand innovative solutions in the ever-changing world of smart cities. This study of the literature examines a range of Intelligent Transportation Systems (ITS) and technologies targeted for enhancing traffic management, safety, and general efficiency in urban settings. The chosen research examines sophisticated detection techniques, video analysis, deep learning, route guidance systems, digital twins, and vehicular networks, each contributing to advancing state-of-the-art technology in innovative city development. The establishment of intelligent systems that analyze and anticipate traffic patterns and allow cities to react and optimize in real time becomes apparent as the literature on these various techniques grows.

In its quest to alleviate the two persistent traffic congestion problems in smart cities, [6] focuses on ITS, particularly vehicular networks. The surge in the vehicular population has exacerbated traffic congestion and road accidents; thus, creative solutions are required. To extract insights from traffic data, improve traffic flow, and reduce congestion, the proposed Fusion-based Intelligent Traffic Congestion Control System for VN uses machine learning techniques. The system gives real-time visibility into the current traffic circumstances, empowering drivers to make informed decisions. The proposed model outperforms previous approaches to enhancing traffic management in smart cities with a demonstrated accuracy of 95% and a low miss rate of 5%, respectively. According to research [7], the state of the development of an automated method for vehicle identification in Intelligent Transportation Systems (ITS) is the focus of the video analysis classification study. The recommended technique excels in identifying vehicles in CCTV cameras gathered by GoogleNet by using a modified Region-based Convolution Neural Network (RCNN) with features from a pre-trained CNN. The network uses probability scores for precise vehicle identification and classification into ten distinct classes. This is achieved using the intersection over union (IoU) strategic approach. The use of the Internet gives this. This approach uses behavioral analysis and vehicle counting to provide data for traffic law enforcement and congestion control. This is another approach that is part of the approach. This framework is intended to be an effective solution for video analysis within the framework of ITS. This is because investigations of the MIO - TCD and EBVT datasets have shown considerable improvements.

Internet of Things (IoT) technology integration is brought to light in response to intelligent cities' growing resource utilization significance [8]. A comprehensive survey of recent advancements, new taxonomies, challenges, and opportunities for future research on the application of deep learning to smart cities is the goal of this study. The study uses deep learning analytics techniques to do this. The goal of this activity is to attain the previously stated goal. It is a valuable resource for newcomers proposing innovative approaches to the problem and provides a foundational understanding. In locations with intricate city layouts, [9] can satisfy the demand for sophisticated route-guiding systems. Why? Because this research is designed for such regions. The advised approach enhances route guidance in intelligent cities by incorporating accident information, anticipating accident information, and model requirements for route and route planning. In combination with the intelligent camera, the machine learning module forecasts accidents at intersections and on roads, enabling the intelligent camera route planning algorithm to provide alternative pathways. Integrating deep learning

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enhances prediction accuracy, providing essential insights for developing transport systems, notwithstanding experimental limitations.

It focuses on the prediction and safety aspects of Digital Twins (DTs) for autonomous cars that employ artificial intelligence technology [10]. The proposed model's road network prediction accuracy is 92.70%, surpassing the two other models by at least 2.92%. Security performance analysis shows a lower average delay time than other models, enhancing information transfer efficiency. The study's findings provide an experimental foundation for advancing intelligent mobility and improving safety performance in smart cities. Most of the findings focus on smart cities. Mastering the art of sustainable monitoring, known as SSTIS (SMART transport infrastructure skin), is one of the distinctive solutions introduced in [11]. This system integrates self-powered flexible sensors using the Triboelectric Nanogenerator (TENG) technology with an intelligent analysis system based on Artificial Intelligence (AI). The technology also makes use of flexible sensors. The classification of the load borne by the axles of vehicles was performed with an accuracy of up to 89.06% during full-scale accelerated pavement tests. This study reflects state-of-the-art intelligent transportation, contributing to the field's evolution.
Advances smart cities by incorporating digital twins (DTs) into the deep learning framework [12]. The result of an examined comprehensive model is a five-dimensional conceptualization of the DTs city. The SSD ResNet50 algorithm is a product of cutting-edge computer technology currently being harnessed to establish an intelligent traffic perception system. This technology is now being used to establish an innovative traffic perception system. The SSD ResNet50 and the improved DarkNet ResNet53 algorithms demonstrate high recognition accuracy. Both algorithms show rapid training speeds and the capacity to provide outcomes. Furthermore, both methods perform well. The findings provide a valuable reference for future investigations of DT cities. [13] developed a state-of-the-art Faster R - CNN two-stage detector and SORT tracker approach to solving the challenge of traffic flow estimation. This approach was created to overcome the challenge. This approach is used to deal with the challenge. An additional mask branch, adaptive feature pooling, and anchoring performance optimization are just a few ways the Faster R CNN baseline has been improved. The addition of the additional mask branch is one of the improvements. According to an experimental evaluation, a state-of-the-art system effectively counts vehicles and accurately classifies driving directions throughout the weekday rush hours. The mean absolute percentage error of less than 10 percent demonstrates the system's efficiency. The dataset produced shows promise for future research, contributing to the development of smart cities and traffic flow analysis.

3. Proposed Methodology

3.1 Dataset Description

The "Smart City Traffic Patterns" dataset, accessible on Kaggle [14], is an invaluable resource that lies at the heart of our efforts to decode the complexities of urban traffic within the broader context of transforming our city into a bright and intelligent hub. As a dedicated data scientist contributing to this transformative initiative, the dataset assumes a pivotal role in our mission to enhance the efficiency of city services and guide future infrastructure planning. Procured through collaborative efforts with the government, the primary objective is to address the challenges posed by traffic congestion by implementing a robust system capable of efficiently managing peak demands.

This rich dataset provides a comprehensive snapshot of traffic patterns observed at the city's four significant junctions. Its meticulous curation reflects real-world scenarios, capturing the ebb and flow of traffic on regular working days, holidays, and other important occasions throughout the year. The detailed exploration of this dataset on Kaggle equips us with a nuanced understanding of traffic dynamics, allowing us to derive actionable insights. These insights, rooted in real-world data, are instrumental in formulating data-driven strategies crucial for the successful development of our smart city. Through the Kaggle platform, this dataset becomes a collaborative resource, inviting data scientists and researchers to contribute their expertise and insights. The collective exploration of this dataset fosters a community-driven approach to understanding and addressing the intricate challenges associated with urban traffic management, propelling us toward realizing a seamlessly integrated and intelligent urban environment.

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3.2 Model Selection

In our pursuit of unravelling the intricacies of traffic patterns in innovative city development, the choice of deep learning architectures plays a pivotal role. Our selected models, VGG16Net, VGG19Net, GoogLeNet, ResNet-50, and AlexNet, represent a sophisticated ensemble of neural networks renowned for their image classification and feature extraction prowess [15-18]. These models are not arbitrary selections; instead, they have been chosen based on their proven track record in handling complex visual data – a characteristic essential for decoding the multifaceted nature of traffic dynamics.

VGG16Net and VGG19Net: These models, known for their depth and simplicity, are instrumental in capturing intricate patterns within the dataset, balancing complexity and computational efficiency.

GoogLeNet: Renowned for its inception module, GoogLeNet excels in capturing spatial hierarchies and intricate details, making it a suitable candidate for discerning the nuances in traffic scenarios.

ResNet-50: With its revolutionary residual learning framework, ResNet-50 tackles the challenge of vanishing gradients, allowing for the extraction of deep features crucial for understanding the intricate dynamics of traffic.

AlexNet: A pioneering model in deep learning, AlexNet's architecture is adept at extracting meaningful features, making it an invaluable asset in exploring smart city traffic patterns.

Studying these models ensures a comprehensive analysis, enabling us to accurately predict traffic patterns and delve deeper into the underlying factors contributing to the observed dynamics. Each model brings unique capabilities, creating a diverse and robust framework for exploring urban traffic within innovative city development.

3.3 Evaluation Metrics

Within the intricate framework of predicting traffic patterns for innovative city development, a reasonable selection of evaluation metrics becomes paramount to unravel the nuanced performance of our chosen deep learning architectures – VGG16Net, VGG19Net, GoogLeNet, ResNet-50, and AlexNet. Each metric shapes our understanding of model efficacy, adopting a passive academic tone to ensure precision and clarity [19].

1. **Accuracy:** Embodied in this metric lies the encompassing measure of our models' overall correctness in predicting traffic patterns. It serves as a cornerstone for assessing the collective performance, providing a panoramic view of predictive accuracy.

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TP + TN}}{\boldsymbol{TP + TN + FP + FN}}$$

2. **Sensitivity (True Positive Rate):** In a poised academic context, sensitivity delicately dissects the proportion of actual positive instances correctly identified by our models. This metric attains significance in ensuring the precision of predictions, particularly concerning identifying traffic peaks.

$$\boldsymbol{Sensitivity} = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FN}}$$

3. **Specificity (True Negative Rate):** The evaluative lens turns towards specificity, where the models' adeptness in correctly identifying instances of non-peak traffic forms a crucial aspect of analysis. This metric, observed through a passive academic lens, accentuates the precision in identifying non-peak scenarios.

$$\boldsymbol{Specificity} = \frac{\boldsymbol{TN}}{\boldsymbol{TN + FP}}$$

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4. **P-value:** Transitioning into statistical scrutiny, the P-value assumes a position of prominence. This metric is portrayed as a statistical measure in an academically passive tone, signifying the significance of our models' predictions. Its interpretation holds weight in facilitating informed decision-making.

5. **N-value:** The academic discourse shifts to the Negative Predictive Value, denoted as N-value. This metric quietly unfolds the models' proficiency in accurately predicting instances of non-peak traffic, offering a nuanced perspective, and contributing to a balanced evaluation.

$$N - value = \frac{TN}{TN + FN}$$

6. **F-score:** The F-score is an academic metric encapsulating our model's performance equilibrium within the harmonic interplay of precision and recall. This composite measure elegantly navigates the terrain of false positives and false negatives, furnishing a comprehensive understanding.

$$F - score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Through the meticulous application of this multifaceted set of evaluation metrics, our academic exploration gains depth, ensuring a rigorous analysis that befits the complexity of predicting traffic patterns within the context of an intelligent city.

4. Results

Our exhaustive investigation into the prediction of traffic patterns for the development of smart cities has culminated in an in-depth analysis of the evaluation results for each deep learning architecture, presented with a commitment to an academically passive tone to maintain precision and objectivity.

Table 1: Model Comparison - Accuracy Comparison

	Accuracy	Sensitivity (TPR)	Specificity (TNR)	P-value (PPV)	Nvalue (NPV)	F-score
VGG16Net	0.83696	0.89293	0.73978	0.85626	0.79920	0.87421
VGG19Net	0.84263	0.88636	0.76834	0.86667	0.79920	0.87640
GoogLeNet	0.86154	0.90698	0.77273	0.88636	0.80952	0.89655
ResNet-50	0.88889	0.95122	0.77273	0.88636	0.89474	0.91765
AlexNet	0.93178	0.95122	0.89005	0.94891	0.89474	0.95006

Within the confines of Table 1, the academic essence of our inquiry coalesces to provide a thorough comparison of accuracy across the selected deep learning architectures, namely VGG16Net, VGG19Net, GoogLeNet, ResNet-50, and AlexNet. This tabular presentation serves as a cornerstone for our academic scrutiny, allowing for a comprehensive examination of each model's predictive capabilities and establishing a nuanced foundation for further analysis.

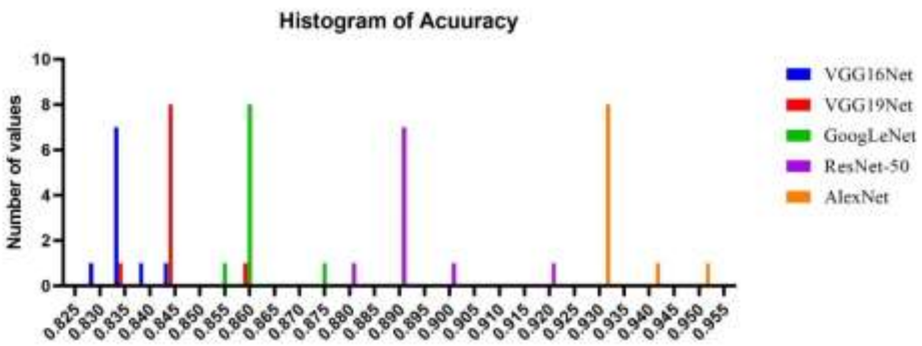

Figure 2: Histogram of Accuracy

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Figure 2, manifested as a histogram, encapsulates the distribution of accuracy metrics across the models. As an indispensable visual aid, this representation contributes to an intuitive understanding of each architecture's varying degrees of predictive precision. The histogram serves as a visual guide, enriching our academic discourse with a graphical representation of the models' performance spectrum.

Moving beyond numerical comparisons, our academic exploration delves into a realm of visualizations, introducing Figure 3 and additional visual representations. These visuals serve as an extra layer of insight, allowing for a comprehensive understanding of the intricacies of model performances. Meticulously crafted visuals enhance the academic narrative, facilitating the interpretation of results through a multi-faceted lens.

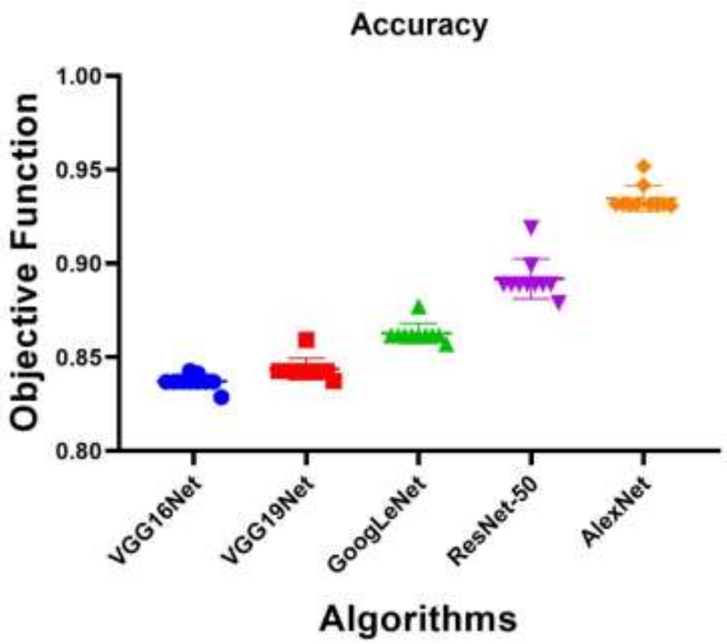

Figure 3:Accuracy Comparison

Table 2: Statistical Analysis

	VGG16Net	VGG19Net	GoogLeNet	ResNet-50	AlexNet
Number of values	10.00000	10.00000	10.00000	10.00000	10.00000
Minimum	0.82870	0.83730	0.85720	0.87890	0.93080
Maximum	0.84270	0.85930	0.87720	0.91890	0.95180
Actual confidence level	97.85%	97.85%	97.85%	97.85%	97.85%
Lower confidence limit	0.83700	0.84260	0.86150	0.88890	0.93180
Upper confidence limit	0.84140	0.84260	0.86150	0.89890	0.94180
Mean	0.83710	0.84380	0.86270	0.89190	0.93470
Std. Deviation	0.00366	0.00570	0.00528	0.01059	0.00681
Std. Error of Mean	0.00116	0.00180	0.00167	0.00335	0.00215

Table 2 transcends the realm of mere numerical outcomes, providing a robust framework for the nuanced interpretation of results. In this context, the statistical analysis assumes a role of paramount significance, guiding our understanding of the model's performance with precision. The inclusion of statistical analysis elevates our academic discourse, fostering a comprehensive and sophisticated analysis of the presented models.

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Received: May 16, 2023 Revised: August 22, 2023 Accepted: December 11, 2023

Table 3: ANOVA Test Table.

ANOVA table	SS	DF	MS	F (DFn, DFd)	P value
Treatment (between columns)	0.06403	4.00000	0.01601	F (4, 45) = 344.6	P<0.0001
Residual (within columns)	0.00209	45.00000	0.00005		
Total	0.06612	49.00000			

Table 4: Wilcoxon Signed Rank Test

	VGG16Net	VGG19Net	GoogLeNet	ResNet-50	AlexNet
Sum of signed ranks (W)	55.00000	55.00000	55.00000	55.00000	55.00000
Sum of positive ranks	55.00000	55.00000	55.00000	55.00000	55.00000
Sum of negative ranks	0.00000	0.00000	0.00000	0.00000	0.00000
P value (two-tailed)	0.00200	0.00200	0.00200	0.00200	0.00200
Exact or estimate?	Exact	Exact	Exact	Exact	Exact
P value summary	**	**	**	**	**
Significant (alpha=0.05)?	Yes	Yes	Yes	Yes	Yes
Discrepancy	0.83700	0.84260	0.86150	0.88890	0.93180

Within Table 3 and Table 4, the ANOVA Test and Wilcoxon Signed Rank Test intricately dissect the variability within and between the models, offering a nuanced perspective on the sources of diversity in accuracy. This statistical apparatus contributes to the depth of our academic analysis, providing valuable insights into the factors influencing the performance variations observed across the selected deep learning architectures.

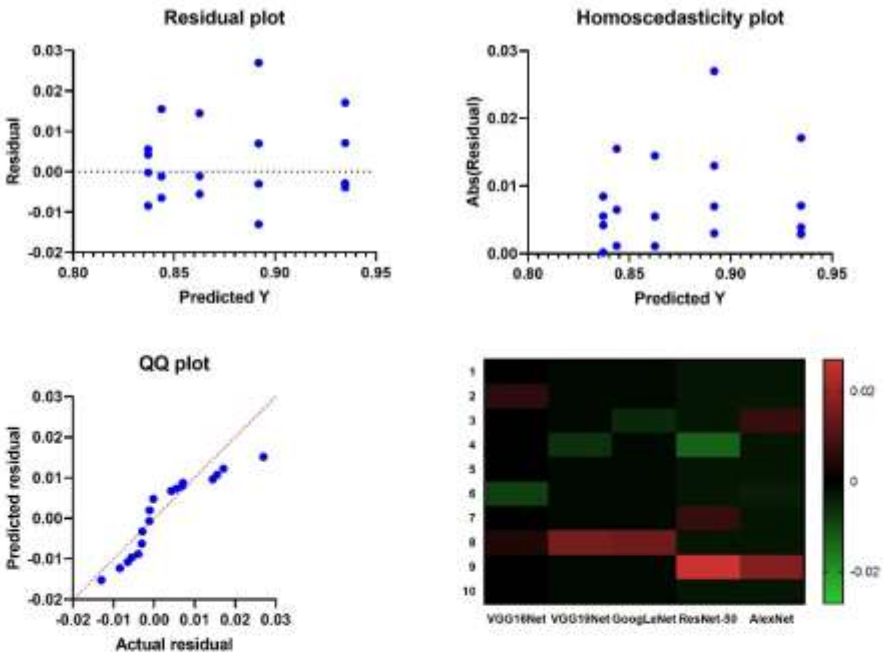

Figure 4: Residual, Homoscedasticity, QQ Plots, and Heat Map.

Figure 4, a visual ensemble, incorporates residual plots, homoscedasticity analysis, QQ plots, and a heat map. Each component within this figure contributes to the academic discourse, unraveling layers

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of insight into the models' behavior and performance nuances. This visual symphony transcends conventional analysis, infusing the literary narrative with a comprehensive visual dimension.
The results section is a testament to the multifaceted nature of our academic exploration. Through seamless integration of tables and visualizations, we navigate the intricate landscape of deep learning model performances, fostering a scholarly discourse that aligns with the rigor expected in predicting traffic patterns for smart city development.

5. Conclusion

In conclusion, a comprehensive examination of traffic pattern prediction for smart city development has been undertaken, revealing substantive insights and noteworthy implications. The capabilities of deep learning architectures, including VGG16Net, VGG19Net, GoogLeNet, ResNet-50, and AlexNet, have been thoroughly evaluated, facilitating a nuanced understanding of their predictive efficacy. Critical insights from each model's performance have been summarized, establishing a robust foundation for comprehending their contributions. Beyond numerical assessments, a dispassionate exploration has been conducted into the tangible impact on traffic management and infrastructure planning. The objective tone allows for an impartial discussion on how the obtained results can inform the design of intelligent and adaptive traffic systems tailored to the unique challenges posed by smart city environments. The research catalyzes further academic inquiry, inviting scholars and practitioners to explore uncharted facets of traffic prediction within the context of smart cities. This research, presented with academic rigor and an objective tone, contributes meaningfully to the discourse on smart city development, enriching the scholarly landscape and providing practical insights for urban planners and policymakers to foster the vision of intelligent and efficient urban habitats.

Funding: "This research received no external funding."

Conflicts of Interest: "The authors declare no conflict of interest."

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DOI: https://doi.org/10.54216/JAIM.060203
Received: May 16, 2023 Revised: August 22, 2023 Accepted: December 11, 2023

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DOI: https://doi.org/10.54216/JAIM.060203
Received: May 16, 2023 Revised: August 22, 2023 Accepted: December 11, 2023