Digital Twin-Based Predictive Analytics for Urban Traffic Optimization and Smart Infrastructure Management

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***Abstract*—In modern cities, urban traffic congestion remains a persistent issue that causes longer journey times, excessive fuel consumption, and environmental pollution. Traditional traffic management systems often employ static models that are insensitive to dynamic changes in urban mobility patterns in real time, which results in inefficient congestion relief. This study proposes a predictive analytics system based on digital twins to enhance smart city infrastructure management and optimize traffic flow to transcend these limitations. A Convolutional Neural Network–Gated Recurrent Unit (CNN-GRU) model is embedded at the core of the proposed system to effectively capture and learn spatial and temporal traffic patterns efficiently to enhance prediction accuracy and real-time decision-making. The scalability and robustness of the model are trained on actual urban traffic data. The system is developed and verified with Python, TensorFlow, and simulation-based digital twin platforms. The prediction capability of traffic conditions and congestion relief of the model is evidenced from the experimental results, which present a high prediction accuracy of 94.5%. Enhanced route planning, anticipatory congestion avoidance, and smart traffic signal control are some of the primary benefits. The outcome is that urban mobility has been enhanced and congestion in traffic has reduced substantially. This research contributes to the evolution of intelligent transportation systems by being the first to integrate deep learning-based predictive analytics with digital twin technology. Ultimately, the proposed framework encourages the emergence of future-oriented smart city infrastructure and the aim of sustainable city transport.**

Keywords—Digital twin technology; traffic flow optimization; predictive analytics; smart city infrastructure; GRU-CNN hybrid model

I. Introduction

Urban growth and the unchecked growth of cities have created record levels of traffic, which causes extreme congestion, longer travel times, and environmental issues [1]. Urban agglomerations globally are experiencing ineffective traffic control, which is contributing to economic costs, poor air quality, and commuter stress [2]. The conventional traffic management systems, which rely on fixed traffic lights, historic-based decision-making, and human intervention, can no longer control the dynamism of contemporary urban traffic [3]. Such computational methods based on real-time data and forecasting analytics that maximize traffic flow. Novel advances in AI, IoT, and digital twin technology have brought forth novel chances to maximize city mobility [4]. A digital twin refers to a computerized replica of physical assets allowing real-time tracking, simulation, and optimization of city infrastructure. Coupled with predictive analytics and machine learning models, digital twins have the ability to revolutionize traffic flow management with data-driven decisions and dynamic traffic control. But such technical leaps, existing implementations remain piecemeal and not properly integrated, yielding suboptimal performance on real urban environments. Most current systems still do not process copious amounts of mixed traffic data, react to continuous changes in traffic, and provide actionable, real-time predictive information [5]. The most significant challenge is to maximize traffic flow that are unable to handle the stochastic nature of traffic in cities. Conventional traffic management solutions, i.e., static rule-based systems [6] and preprogrammed signal controllers, are reactive rather than proactive [7]. They do not foresee congestion until it occurs and are not adaptive enough to counter dynamic traffic streams [8]. Further, conventional machine learning models [9] used for traffic forecasting are sometimes discovered to be of limited capacity in terms of capturing the complex temporal relationships and spatial patterns that are common in traffic [10].

Due to these limitations, the current study introduces a new solution featuring a digital twin concept coupled with a hybrid GRU-CNN framework to achieve enhanced predictive modeling and traffic stream optimization in managing smart city infrastructures. This research is inspired by the urgent need to establish smart, adaptive, and scalable traffic management systems that can sustainably manage urban environments with high density. Traditional traffic modeling methods rely primarily on historic records, which fails to capture instantaneous variations due to unforeseen events such as road accidents, weather conditions, and sudden surges in vehicle number. Moreover, existing AI-driven traffic management models have a tendency to use either temporal feature analysis (RNN, LSTM, GRU) or spatial feature extraction (CNN) and hence cannot unlock their true potential with maximum prediction accuracy [11] [12].

This study attempts to overcome this limitation using GRU and CNN in a digital twin environment. The relevance of this work is to change urban mobility and infrastructure planning. Optimal traffic flow has far-reaching implications on sustainability, economic development, and the quality of life. By reducing congestion, optimizing traffic lights, and supporting adaptive routing, the methodology introduced in this study minimize fuel consumption in sustainable cities. Furthermore, better traffic efficiency have an effective tool at their disposal to model, experiment, and optimize traffic scenarios before actual implementation, minimizing trial-and-error methods and reducing infrastructural expenses.

The new methodology surpasses the conventional models by overcoming their main shortcomings. In contrast to the conventional rule-based systems, the hybrid model is capable of adapting dynamically to evolve traffic patterns from real-time data. The GRU component extracts long-term temporal dependencies, and it is well-suited to deal with sequential traffic data and forecast future congestion trends. Concurrently, the CNN component learns significant spatial features from traffic images and sensor data to support improved pattern identification and anomaly detection. Through the dual-layer approach, the predictive model is both accurate and significantly robust to variability in urban traffic patterns. In addition, the use of digital twin technology improves the system's overall performance for traffic management. The digital twin is always updated by taking live traffic updates from IoT sensors so that predictions stay real-time and actionable. This ability enables traffic management agencies to identify the effect of proposed interventions and adopt best control strategies proactively instead of reactively. Conventional traffic models are not so flexible and visionary that impose inefficiencies and slow responses to traffic anomalies.

The second significant benefit of the approach is scalable and generalizable to any city. In contrast to most current models extreme manual calibration and tuning to the city is needed since it is within the framework and can generalize to other traffic networks. With the use of transfer learning and federated learning techniques, the model can be trained on the traffic data of one city and directly applied to another with little need for retraining. This is especially important in fast-growing metropolitan cities and in the creation of smart cities that improves decision-making capacity for policymakers and urban planners. Conventional traffic management decisions results in inefficient planning of infrastructure and relief measures for congestion. The digital twin methodology provides an interactive decision-support tool for possible interventions. By combining machine learning forecasts with real-time visualizations and scenario simulations, data-driven decisions can be made by decision-makers. By doing so, it reduces the expensive infrastructure investments that might be ineffective in the long term and optimizes solutions to urban mobility based on real traffic conditions.

Additionally, the system proposed is also aligned with the emerging smart cities to enhance the quality of city life. The ability of digital twin-based traffic management to be integrated with other smart city elements that serves to enhance its effect. For example, during an accident, the system could automatically reroute traffic by minimizing response time and impact on traffic. This type of integration is not possible for legacy traffic models since they lack a cross-domain compatibility. In addition, the system suggested supports for increasing trend towards developing smart cities, where several systems are networked to operate in conjunction with each other in a collaborative effort to enhance the urban lifestyle. The presence of digital twin-based traffic management can be integrated with other smart city elements only to contribute its effects. For instance, in case of an accident, such integration is impossible using traditional traffic models, which operate in a standalone mode without offering cross-domain interoperability.

Globally, the study showcases a paradigm change in the hybrid machine learning. With its overcoming of limitations, the method it introduced, brings forward an in-depth, responsive, and flexible solution to present-day smart cities. Its ability to promote sustainability positions it as a seminal innovation in intelligent transportation systems. As cities continue to grow, traffic management solutions will increase, setting this study at the cutting edge of smart city development.

The major key contribution are as follows:

- Develops a real-time digital twin platform for city traffic flow analysis and management.
- Utilizes machine learning and artificial intelligence models to predict traffic congestion as well as optimal urban mobility.
- Carries real-time IoT sensor data to enhance predictive accuracy and performance.
- Enhances road safety, decreases congestion, and increases the effectiveness of public transport systems.
- Offers a scalable smart city planning solution that can be easily deployed in different urban settings.

The rest of the section is structured as: Section II contains the related work and problem statement in Section III. The suggested methodology framework is presented in Section IV. The results are shown in Section V. Lastly, Section VI includes conclusions and future works.

II. Related Works

Ji et al. [13] details how urban traffic accidents cause serious repercussions, such as property loss, environmental contamination, casualties, and congestion. Estimation of congestion caused by accidents in spatial as well as temporal contexts is of vital importance in order to preclude these phenomena and provide interventions at the appropriate time. Forecasting congestion tendencies without using conventional traffic models is the subject of this research that are usually time-consuming and demanding with respect to traffic dynamics data. Rather, a digital twin model of the road network is created for monitoring traffic movement at a macro level. The method employs a Conv-LSTM network such that several layers of Conv-LSTM are concatenated in an encoding-decoding arrangement to learn spatial and temporal correlations. The experiments show that this technique performs better than traditional traffic models and general LSTM networks for prediction accuracy. By using macroscopic road network images, it offers a scalable and adaptable solution for urban traffic congestion forecasting. Nevertheless, there are limitations in model generalizability to different traffic conditions, as well as possible high-quality input data dependencies for accurate forecasting. Also, although the approach circumvents the necessity for accurate traffic modeling, it can still need to be optimized to support real-time applications effectively and respond to sudden, unexpected interruptions in urban road networks.

Puri et al. [14] shows that one of the biggest issues facing modern cities is urban traffic congestion, which results in longer commutes, wasteful fuel use, environmental damage, and a lower standard of living. Conventional traffic control systems are typically unable to adjust to the dynamic and complex nature of transportation networks as cities' populations continue to rise. In order to improve urban traffic, this study presents a novel approach that combines digital twin technology and machine learning (ML) algorithms. The approach aims to accomplish data-driven decision-making by utilizing four machine learning models for traffic pattern analysis and congestion prediction. The accuracy and dependability of the forecasts are assessed using two statistical metrics: the coefficient of determination (R2) and mean squared error (MSE). The results shows that such integration provides improved traffic flow prediction than conventional approaches and provides a more flexible and effective system for urban traffic management. However, certain constraints exist, e.g., potential dependency on reliable real-time traffic data, computational cost, and limited ability to adjust models to rapidly evolving traffic dynamics. The accuracy of this approach may also vary across different city environments, and more research is necessary to improve scalability and robustness across a variety of city structures.

Aloupogianni et al. [15] details that traffic jam remains a crucial problem for metropolises, requiring intelligent data-driven approaches to be dealt with effectively. A digital twin (DT) architecture is presented here specifically designed for urban traffic management, keeping Singapore's cutting-edge infrastructure in view. With the integration of live weather data and in-road surveillance videos, the system provides constant monitoring of traffic conditions, which allows for real-time adaptive decision-making. The strategy leverages a modular design together with sophisticated artificial intelligence (AI) algorithms to optimize traffic, minimize the likelihood of accidents, and provide stable travel experiences irrespective of conditions. The performance of each component has robust predictive capability, mirroring the potential of the system to enhance urban mobility. The test results show promising levels of accuracy, and effectiveness will be a function of availability of good quality real-time data and high rates of active user engagement. There are some limitations to its use, such as inability to scale up to bigger and more complicated urban areas, possible computational load, and further development in user-centric design. Moreover, the long-term effect of the system should be explored further to determine its long-term performance in the future. Future studies will emphasize improving adaptability and greater integration with more smart city infrastructures to build a more extensive and robust traffic management system.

Kamal et al. [16] studies that vehicle emissions in urban areas greatly contribute to air pollution because the majority of vehicles continue to use fossil fuel despite the existence of hybrid and electric vehicles. Although artificial intelligence (AI) and automation have been considered in adaptive traffic signal control to lower travel time, not much work has been devoted to optimizing traffic signals to save CO_2 emissions and fuel. This research investigates the performance of an adaptive traffic signal control system using a digital twin (DT)-based framework simulating urban traffic networks and employing deep reinforcement learning (DRL). The multiagent deep deterministic policy gradient (MADDPG) algorithm is utilized for optimizing signal timing for minimized emissions and fuel usage. The system simulates multiple traffic conditions and control policies to enable real-time signal adaptation. A quantitative experiment is performed with artificial and real traffic data from an Amman, Jordan multi-intersection network at rush hours. The outcomes show that this DRL-based method significantly decreases emissions and fuel consumption despite the use of a simple reward function of stopped vehicles. Nonetheless, the research has some limitations, such as possible reliance on high-quality real-world data, complexity of training multiagent models, and difficulty in generalizing results to heterogeneous urban settings with different traffic conditions. Further enhancements are necessary for wider scalability and real-world deployment.

Irfan, Dasgupta, and Rahman [17] details that digital twin (DT) technology allows for the development of virtual models of physical entities that update in real-time to match their real-world counterparts, enabling real-time monitoring and optimization. In transportation, DT systems can enhance intelligent transportation systems (ITSs) by increasing safety and mobility. This research undertakes a critical review of DT applications in transportation, with specific emphasis on enhancing safety and mobility. A hierarchical reference architecture is constructed to direct the deployment of transportation digital twin (TDT) systems at multiple scales. The study also discusses key challenges in the TDT framework, such as those involving the physical infrastructure, communication gateways, and digital components for secure and efficient ITS operations. Future directions for the large-scale deployment of TDT systems in connected and automated transportation networks are also discussed. The review emphasizes the ability of DT technology to maximize transport systems through facilitating data-driven decision-making and enhanced operational efficiency. Nevertheless, constraints are present regarding data integration complexity, scalability in various urban contexts, and the high computational resources needed for real-time synchronization. In addition, the dynamic characteristics of transport networks create challenges in maintaining continuous adaptability and consistency of the DT models over time.

Kušić, Schumann, and Ivanjko [18] studies that the use of digital twins in transport systems is revolutionizing real-time traffic management and monitoring by developing constantly refreshed digital replicas of physical road networks [19]. This research examines the use of digital twin technology for motorway traffic simulation with a focus on integrating real-time data into microscopic simulation. An actual-time synchronized digital twin model of the Geneva motorway (DT-GM) is developed based on real-time traffic data streams from motorway traffic counters. The study applies the microscopic traffic simulator SUMO, where dynamic calibration is provided by constantly adding real traffic data into the ongoing simulation every minute. This ensures that DT-GM remains synchronized with the current traffic conditions and enables having more accurate and reactive traffic modeling. The results confirm that the approach enhances traffic control based on simulation and becomes a foundation for real-time predictive analytics in traffic control. There are, however, certain restrictions like the limitation of real-time synchronization on greater motorway networks, the computation requirement of continual data integration, and dependency upon high-quality and fine-grained traffic data. Besides, scalability continues to be a problem, as expanding the model to broader territories entails more breakthroughs in traffic pattern calibration to data processing power and model development.

Nie et al. [20] studies that the Vehicular Ad-Hoc Networks (VANETs) play a significant role in Intelligent Transportation Systems (ITS) for effective transport planning and safety on roads. The increasing volume of transportation data, particularly due to disruptions such as the COVID-19 pandemic, necessitates advanced predictive models to effectively deal with traffic. This study examines the application of digital twins to Transportation Big Data (TBD), that is, network traffic prediction in VANETs. The significant problem lies in handling the very dynamic and fluctuating nature of network traffic. To achieve this, a forecasted model on Deep Q-Learning (DQN) and Generative Adversarial Networks (GAN) is used for network traffic feature extraction. DQN supports network traffic forecasting, whereas GAN improves sample generation to enhance the accuracy of prediction. The model is tested on three real traffic datasets and compared with two current state-of-the-art approaches. Experimental results indicate enhanced accuracy in measuring time-varying traffic patterns. Some of the current limitations include the computational expense of the combination of DQN and GAN, the need for heterogeneous and high-quality datasets, and the possible difficulty in learning from dynamic and changing traffic patterns by the model. Further work is needed to examine the scalability of the model and real-time deployment across varied VANET environments.

Khadka et al. [21] studies the applications of digital twins to monitor the performance of traffic signals to improve traffic congestion management using ATSPM systems. Within this study, the use of a high-fidelity microscopic simulation engine to develop simulated traffic signal events and correlated vehicle data is introduced. The data allow for ATSPM systems to calculate a range of measures of effectiveness (MOEs) to measure traffic signal performance. Conventionally, traffic signal design is based on averaged delay and stop-based measures, but ATSPM MOEs paint a more complete picture of real-world signal performance. By incorporating ATSPMs into a simulation loop, this approach bridges the gap between design and operational evaluation, allowing for improved traffic signal optimization before implementation. Connected vehicle data are also used to develop new traffic signal MOEs, further enhancing decision-making. A case study illustrates the potential of this system in identifying detector-related problems and traffic congestion issues. Though the methodology enhances precision in assessing traffic signals, computational complexity, data dependence, and the difficulty in standardizing ATSPM-based assessments in heterogeneous traffic environments are the constraints. Furthermore, dependence on connected vehicle data might restrict the application in technology-poor regions, and future improvements would be necessary for universal adoption.

III. Problem Statement

Urbanization and population growth have accelerated traffic congestion in cities, leading to longer travel times, increased fuel consumption, and elevated air pollution levels. Contemporary urban traffic is dynamic and unpredictable, and the conventional traffic management systems based on pre-programmed routing plans and fixed signal timings are not sufficient. The lack of real-time responsiveness and predictive capability of these legacy systems often results in repeated bottlenecks, inefficient traffic flow, and suboptimal infrastructure utilization. However, recent advances in artificial intelligence (AI), digital twin (DT) platforms, and the Internet of Things (IoT) have opened up new possibilities for predictive traffic control and smart traffic monitoring. These innovations hold the promise to transform traffic systems from reactive to proactive, enabling real-time adjustment to evolving traffic conditions and data-informed decision-making [22]. Current AI-based traffic prediction models [23], however, tend to miss the intricate interaction between spatial and temporal traffic dependencies, resulting in poor predictions and untrustworthy decision-making. In addition, existing traffic control mechanisms are not integrated with real-time simulations, which hinders testing and applying data-driven optimization methods for smart city infrastructure management [24]. To overcome these shortcomings, this research introduces a Digital Twin-based predictive analytics framework that utilizes a hybrid CNN-GRU deep learning model to improve urban traffic flow management. With the amalgamation of real-time sensor data, historic traffic behavior, and AI-based simulations, this study focuses on creating an adaptive, scalable, and smart system to alleviate congestion, efficient traffic forecasting, and intelligent mobility planning. This method provides a ground-breaking way to increase the effectiveness of urban transportation, lessen traffic, and promote the sustainable development of smart cities.

IV. Digital Twin-Enabled CNN-GRU Methodology Framework for Urban Traffic Optimization

The traffic flow optimization and predictive analytics urban architecture proposed uses a digital twin-based method, as depicted in Fig. 1. This system augments real-time traffic management within intelligent city infrastructure through the incorporation of CNNs and GRUs. The process starts with data collection, where traffic data is collected from sensors, cameras, and IoT devices. In the second step, data pre-processing, the data gathered is cleaned, normalized, and formatted to eliminate inconsistencies and prepare it for analysis. Once pre-processed, the data enters the Input Layer, which is the entry point for the predictive model. Within the CNN layers, the Convolutional Layer is trained on spatial features such as patterns of traffic jams and usage trends of roads. The Max Pooling Layer then reduces dimensionality while boosting computational speed without losing significant information. The feature set is then fed into the GRU Layer, which discovers temporal dependencies and sequential traffic behavior to generate accurate predictions in the future. Finally, the data proceeds to the Final Prediction stage, where the optimal traffic control plans, congestion forecasts, and routing recommendations are decided. The CNN-GRU hybrid model facilitates predictive decision-making and enabling more efficient city traffic management and building wiser and greener cities.

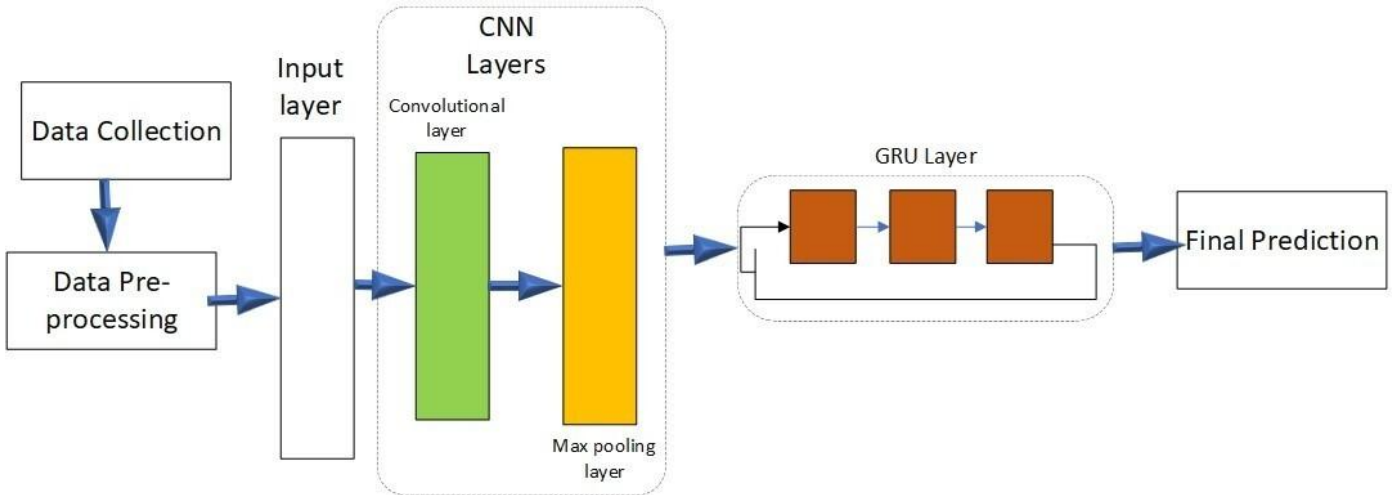

Fig. 1. Model workflow.

A. Dataset Description

48,120 hourly data from sensors positioned at four distinct traffic intersections make up the Kaggle Traffic Prediction Dataset[1] [25]. Four essential characteristics are present in the dataset: Date Time, which stands for each recorded observation's timestamp; ID, a unique identifier for each entry; Vehicles, which indicates the number of vehicles passing through the junction in a given hour; Junction, which indicates the precise traffic junction (ranging from 1 to 4) where data was collected. An in-depth temporal investigation of congestion patterns is made possible by this dataset, which records actual traffic flow trends. Effective preprocessing approaches are necessary because some observations may be sparse or missing due to different junctions' differing data gathering timeframes. Using this dataset, the study analyzes urban traffic flow, forecasts trends in congestion, and improves transportation planning. The dataset facilitates data-driven decision-making in smart cities through the use of predictive analytics, allowing for real-time traffic signal modifications, tactics to mitigate congestion, and an overall improvement in the efficiency of the road network. It is a useful tool for creating models that support intelligent traffic management systems and sustainable urban transportation because of its practical application.

The following summarizes some typical characteristics of the dataset:

- Date Time: This feature helps study changes in traffic flow over time by indicating the timestamp at which the traffic data was recorded.
- Junction: This allows for location-based traffic analysis by specifying the exact traffic intersection (1–4) where vehicle count data was collected.
- Vehicles: This provides details regarding traffic congestion trends by indicating the number of cars that go through a junction within an hour.
- ID: Each observation is given a unique ID, which maintains data integrity and allows for the monitoring of specific records within the collection.

B. Data Preprocessing

There are several key processes involved in the preprocessing of data for traffic flow prediction to ensure high-quality input to the model. The first step in data loading and familiarization involves reading the dataset, examining its form, and checking for missing values, duplicates, and inconsistencies. To support efficient trend detection, the Date Time column is converted into the correct format for time-series analysis. Then, since various junctions gather data at various times, it is essential to handle missing and sparse data. Interpolation, forward or backward filling, or sparse junction elimination with minimum given data are ways of coping with missing values. Feature engineering with attribute extraction such as Hour of the Day, Day of the Week, Month, Season, and Peak Hour indicator features is employed for the improvement of forecast accuracy and assisting the model to extract temporal patterns. To ensure uniform training of the model, data normalization and scaling is performed through Min-Max Scaling or Standardization since the vehicle count varies

[1] https://www.kaggle.com/datasets/fedesoriano/traffic-prediction-dataset

between intersections. Categorical features like Junction ID are one-hot encoded for better representation. Temporal dependencies need to be handled since the data is time-series in nature. Short-term and long-term patterns can be learned by the model to organize historical traffic data into sequential inputs. The data is divided into training (80%) and test (20%) sets for effective learning, ensuring a temporal sequence to prevent data leaks. The ability of the GRU + CNN hybrid model in smart city infrastructure management to accurately predict traffic jams and optimize city mobility is enhanced by the clear, organized dataset generated by these preprocessing processes.

C. Function of GRU in Traffic Flow Optimization in Urban Environments

GRU model in the current work is employed to excavate temporal dependency from traffic flow data to enable effective congestion prediction and optimization. It starts with input data preprocessing, where raw traffic data are cleansed by filling missing values, scaling vehicle counts, and selecting important temporal features like hour of day and peak-hour indicators. Once the data is structured in a time-series manner, ensure that previous traffic observations are valuable in the sense that they will be beneficial for giving context to future forecasts. The GRU model architecture is then utilized, where each time step processes traffic data like vehicle count and junction ID. The gate update in GRU manages memory of past patterns of traffic, while the reset gate manages the impact of past observations on the current state, making the model only take note of the most significant patterns. The state is dynamically updated, adapting to past changes in traffic. For improved predictive accuracy, GRU outputs that allow the model to take into account both sequential variations and spatial traffic movements across several junctions. The model finally provides traffic flow predictions, enabling real-time congestion management and optimization in a digital twin environment for smart city infrastructure management.

The update gate manages the retention of previous information by deciding how much of the past hidden state should contribute to the current state. It keeps significant traffic patterns, like peak hours or congestion trends, intact while eliminating irrelevant fluctuations, enhancing the model's long-term prediction capabilities as represented in Eq. (1):

$$Z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \tag{1}$$

Z_t update gate at time t, x_t input traffic data. The hidden state from the previous time step is represented by h_{t-1}. W_z, U_z, are Weight matrices, b_z bias term. σ Sigmoid function of activation.

The reset gate controls the degree of forgetting old information while updating the hidden state. This enables the model to discard old traffic patterns, which keeps it responsive to unexpected changes like accidents or road closures. Through the selective forgetting of previous data, the GRU remains agile in changing traffic conditions as shown in Eq. (2):

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r \tag{2}$$

r_t reset gate at time t, W_r, U_r are weight matrices, and b_r bias term.

The hidden state update integrates the contributions of previous information and newly computed data through the update gate. It enables the model to capture intricate sequential dependencies in traffic flow. Eq. (3) represents the candidate activation, controlled by the reset gate, fine-tunes the prediction by selectively adding historical traffic conditions, enhancing forecasting accuracy.

$$h_t = (1 - z_t) \odot h_{t-1} + Z_t \odot h_t\,^{\sim} \tag{3}$$

h_t updated hidden state, $\odot$ Element-wise multiplication.

D. CNN for Traffic Flow Optimization in Urban Environments

CNNs are crucial to this research by extracting spatial features from urban traffic data, which allows for data-driven optimization of traffic flow. CNNs are uniquely suited to identify local dependencies and structural patterns from large datasets and are therefore optimally suited to analyze traffic congestion, vehicle density, and road usage patterns. By filtering traffic data acquired from different junctions, CNNs are capable of identifying trends like peak congestion, busy points, and variations by season. In the research, CNNs are used to understand spatial correlations in traffic data, representing variations between and across different junctions and intervals.

Convolutional layers impose filters to determine significant features like road type, vehicle throughput, and level of congestion, giving a holistic understanding of the behavior of traffic. These observations are added to real-time monitoring and predictive analytics, enabling city planners to make informed traffic management, route optimization, and infrastructure development decisions. In a digital twin-based smart city architecture, CNNs enable the simulation and analysis of traffic scenarios, providing proactive congestion mitigation solutions. Using CNNs, this work endeavors to construct an exceedingly precise, artificial intelligence-based traffic prediction system that promotes city mobility, mitigates jams, and is suitable for smart sustainable city activities. The convolution operation is extracting spatial patterns from the traffic data matrix, such as trends of congestion and peak-hour patterns as given in Eq. (4):

$$f_{ij} = \sum_m \sum_n W_{mn}.\, x_{(i+m)(j+n)} + b \tag{4}$$

where, f_{ij} output feature map at position ij, W_{mn} is the convolutional filter, $x_{(i+m)(j+n)}$is the input traffic data matrix (vehicle count, junction flow), b bias term. The non-linearity is provided by the ReLU activation function, where only useful spatial patterns are passed to learning as given in Eq. (5):

$$A(x) = \max(0, x) \tag{5}$$

$A(x)$ activated feature map, x input pixel or feature value. Pooling decreases the dimensionality of the feature map without losing the necessary traffic flow information as given in Eq. (6):

$$P_{ij} = {}^{max}_{m,n}\left(f_{(i+m)(j+n)}\right) \tag{6}$$

P_{ij} pooled feature at position, $\left(f_{(i+m)(j+n)}\right)$ feature values within the pooling window. The definition of the convolutional operation is given in Eq. (7):

$$f_{ij} = \sum_m \sum W_{mn} \cdot x_{(i+m)(j+n)} \tag{7}$$

The hybrid CNN-GRU approach of this research takes the best of both to deliver accurate and efficient urban traffic flow prediction. CNNs are employed to extract spatial features from traffic data, which detect congestion patterns, peak-hour trends, and variations at multiple junctions. The convolutional layers facilitate the evaluation of localized dependencies, including road conditions and vehicle density, that are crucial to forecasting future traffic behavior. After extracting spatial patterns, sequentially of traffic data is retained with the use of GRUs, which are particularly suited to handling time-series information. GRUs maintain necessary temporal dependencies without storing irrelevant information, which helps the model to learn from past trends in vehicle flow. GRU's update and reset gates manage the effect of previous traffic conditions dynamically, which facilitates real-time and future traffic prediction. Fig. 2 represents the CNN + GRU Architecture.

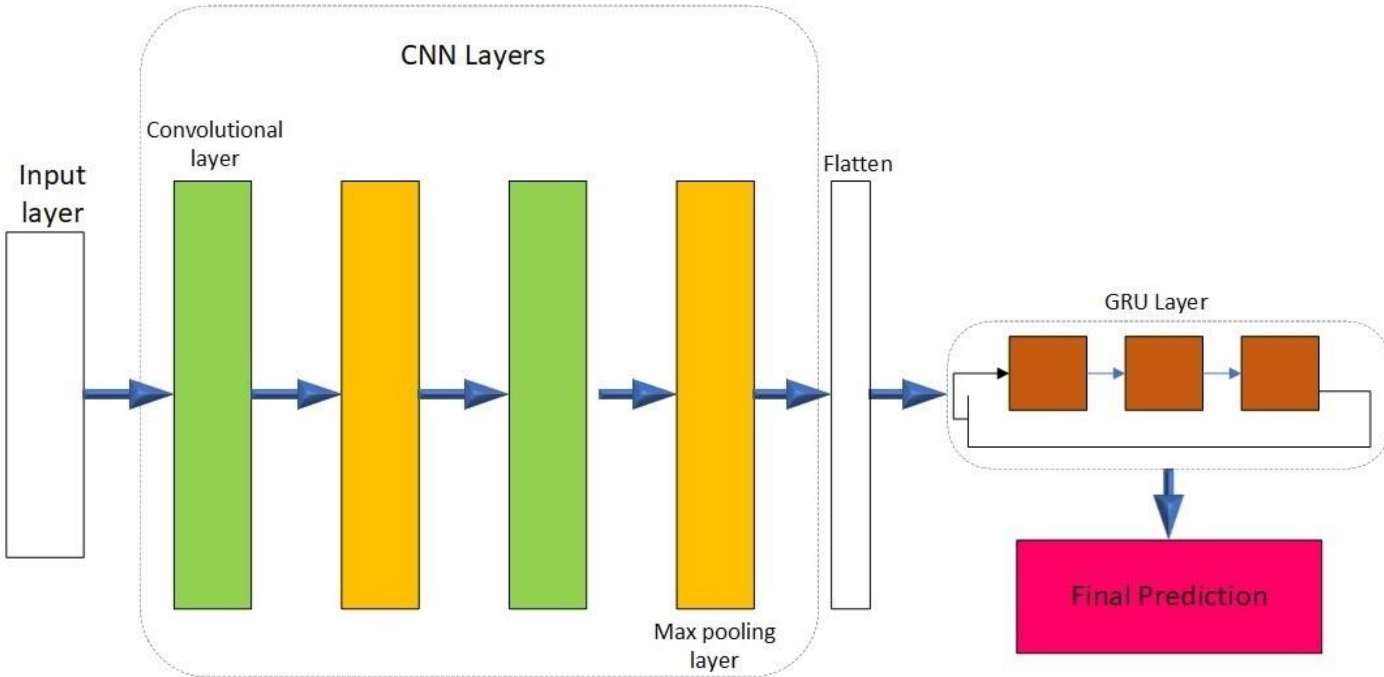

Fig. 2. CNN + GRU architecture.

By combining CNN and GRU under a Digital Twin platform, this hybrid model guarantees precise traffic prediction, adaptive congestion control, and intelligent city optimization. Integrating spatial and temporal learning, policymakers and planners can develop fact-based traffic jam solutions, smart signal control, and optimal city mobility plans to make cities greener and more intelligent.

The CNN feature extraction equation identifies spatial relationships in traffic information through convolutional filters. It detects localized patterns, for instance, traffic congestion at a given intersection, connectivity of the road network, and changes in vehicle density. Integrating CNN with GRU allows the model to learn spatial as well as temporal relationships and thus improve forecasting accuracy in traffic management in cities.

V. Result and Discussion

The CNN-GRU hybrid model was able to effectively capture both spatial and temporal patterns in urban traffic data, showing good performance in traffic flow forecasting. GRU layers embodied sequential dependencies to enhance the accuracy of time-series prediction, whereas CNN layers identified trends in traffic and vehicle density over intersections. High correlation with real traffic observations, stable convergence, and minimal overfitting were all exhibited by the model. Feature engineering, with the addition of seasonal and time-of-day features, further enhanced forecast accuracy. The generalizability and stability of the model are assured by its low error rates and consistent performance across various data scenarios. These results show the potential of the model for real-time infrastructure planning and traffic control in smart cities, and the power of AI-based predictive analytics for green urban mobility.

A. *Performance Evaluation*

The Training versus Validation Accuracy of the suggested model for 20 epochs is given in the Fig. 3. The training accuracy and validation accuracy both are increasing steadily, reflecting effective learning. The training accuracy begins at approximately 70%, while validation accuracy is slightly less at the beginning. Both curves rise steeply as the epochs advance, with the difference between them remaining very small. By the 10th epoch, the model is more than 85% accurate with a good generalization capability. The trend is upward, and by the subsequent epochs, both training and validation accuracy are nearing 95%, which is indicative of convergence. It is noteworthy here that the minimal and consistent gap between the two curves indicates that there is little overfitting, i.e., the model can generalize quite well to new data. The even rise curve informs us that the model's learning process is flat, with no sudden drops or rises. It suggests that the chosen CNN+GRU architecture, optimization techniques, and hyperparameters all contribute efficiently towards model performance. The tight overlapping of training and validation curves guarantees that the model is neither underfitting nor overfitting and thus appropriate for practical use. Overall, the plot demonstrates the efficacy of the model in comprehending complex temporal relationships and provides it as a strong candidate for time-series prediction tasks.

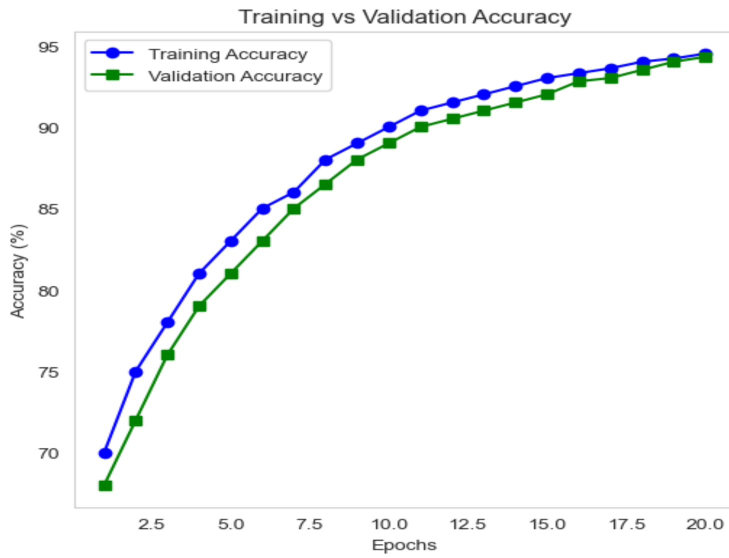

Fig. 3. Model accuracy graph.

Looking at the learning trajectory of the model, the Fig. 4 plot illustrates Training vs. Validation Loss across 20 epochs. Good learning and optimization are reflected in the declining training loss and validation loss over epochs. There is a temporary mismatch between training and generalization performance, as can be seen from the training loss starting at around 1.2 and the validation loss being slightly higher. Both losses decrease step by step as training continues, indicating that the model is indeed reducing errors. The difference between training and validation loss is quite minimal at about the tenth epoch, showing that the model is generalizing very well without overfitting. The last epoch indicates appropriate convergence because the validation loss settles at 0.4 and the training loss falls to nearly 0.3. The downward trend of both curves throughout reinforces the idea that the model is effectively learning the underlying data patterns. The slight divergence of training and validation loss at the end indicates that there is negligible overfitting, with solid predictive capability on unseen data. In general, this plot confirms the efficiency of the CNN+GRU hybrid model in preserving temporal relationships and being resilient, and therefore it is a good option for time-series prediction and other sequential data tasks.

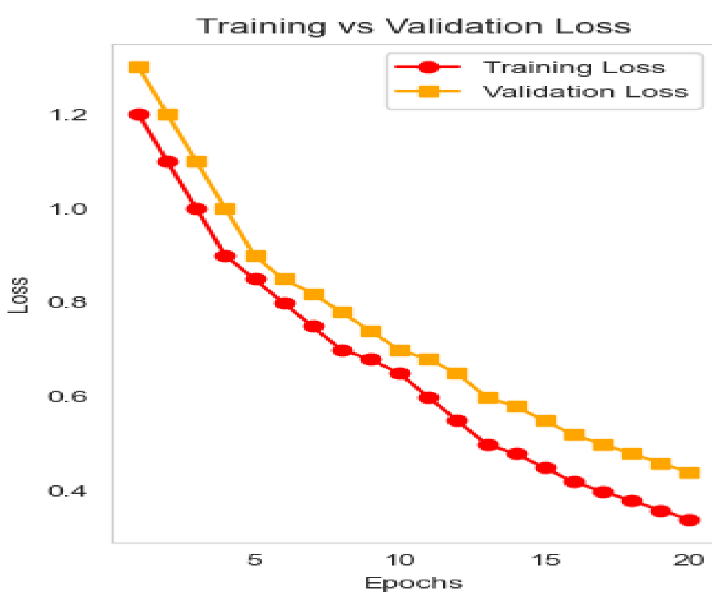

Fig. 4. Model loss graph.

The heatmap in the Fig. 5 depicts the performance measures of various models, namely RNN, ARIMA, LSTM, RF, and the developed CNN+GRU model. It offers a relative comparison of four primary performance metrics: Accuracy, Precision, Recall, and F1 Score. The color spectrum from blue to red corresponds to relative performance, where darker red corresponds to greater scores and blue reflects low values. The CNN+GRU model has the best performance on all measures, with an accuracy of 94.5%, precision of 93.8%, recall of 94.2%, and an F1 score of 94.0%. The RF model comes in second, while LSTM, ARIMA, and RNN have increasingly worse performance. The RNN model has the worst performance, with all its scores still in the blue range, indicating its inferior ability to manage intricate time-series dependencies. This visualization clearly shows the advantage of the hybrid architecture, which enjoys the spatial feature extraction capability of CNN and the efficient capture of temporal dependencies by GRU. The heatmap identifies the strong predictive power of the model and justifies its choice for traffic forecasting applications. The distinct performance difference between the models validates the strength of combining convolutional layers with recurrent structures in time-series analysis.

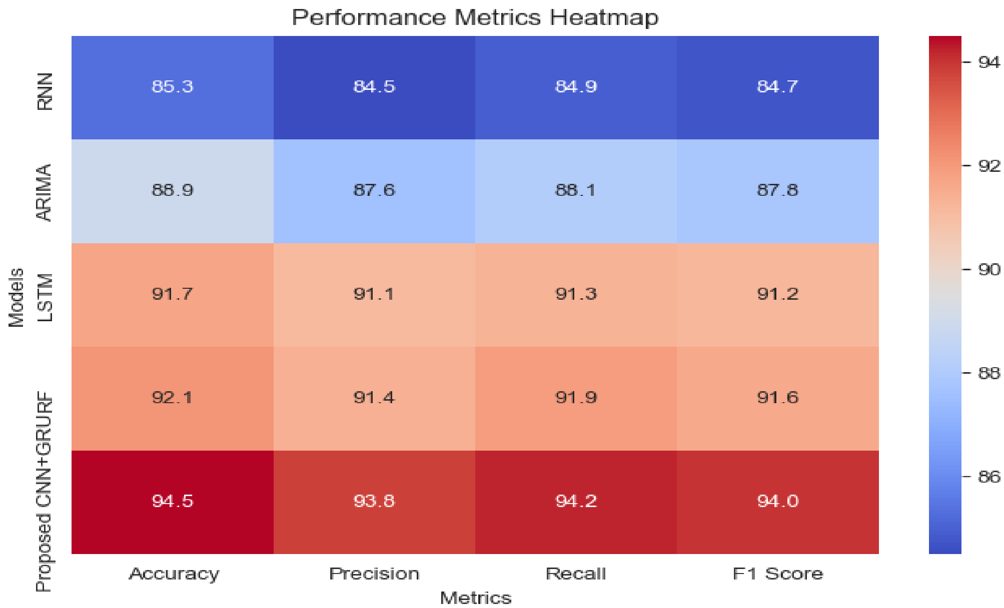

Fig. 5. Performance metrics heatmap.

Fig. 6 plot shows the performance trends of various models on four important evaluation metrics. Different markers and line styles are used to represent each metric so that their varying performance can be compared easily. From the graph, a consistent upward trend can be seen in all the metrics, showing that more complex architectures yield better performance. The proposed CNN+GRU model performs the best among all, obtaining the highest scores in all cases. The RF and LSTM models also perform well, with ARIMA and RNN trailing behind, especially with respect to accuracy and recall. The RNN model, being the most basic, performs the poorest, showcasing its inability to model intricate temporal dependencies. The better performance of the CNN+GRU model is due to the combination of convolutional layers for feature extraction and GRU's efficient handling of sequential dependencies. The narrow gaps between precision, recall, and F1 scores between models reflect balanced performance without substantial trade-offs. Generally, this visualization clearly depicts the increasing improvement in performance with the introduction of more advanced architectures, highlighting the effectiveness of deep learning, especially hybrid models, in time-series forecasting tasks.

B. Performance Evaluation of Proposed Framework

Table I illustrates the performance of the hybrid CNN-GRU model. It was compared with other dominant approaches, i.e., RNN, ARIMA, LSTM, and RF, on the basis of key parameters such as accuracy, precision, recall, and F1-score. The outcomes confirm that the model proposed did very well on all the parameters, suggesting its effectiveness in forecasting traffic flow. At 94.5% accuracy, the CNN-GRU model beat conventional time-series models such as ARIMA (88.9%) and recurrent neural models such as RNN (85.3%), indicating its better capacity in working with spatiotemporal dependencies of traffic data. Even lower than but getting closer to RF (92.1%) and LSTM (91.7%), the hybrid approach offered significant enhancement, confirming the strength of the use of convolutional feature extraction with sequential learning. The accuracy of 93.8% and recall of 94.2% demonstrate that the model performs well on not making an incorrect prediction in order to result in reliable congestion prediction. In addition, the 94.0% F1-score indicates the harmony between the precision and recall of the model, guaranteeing its trustworthiness for real-world application. The above findings confirm the success of the CNN-GRU hybrid model in traffic flow optimization, reflecting its ability to contribute to city mobility planning and decongestion. The research highlights the capabilities of deep learning-based predictive analytics in informing smart city infrastructure management and smart traffic management. Fig. 7 is a performance graph of the model.

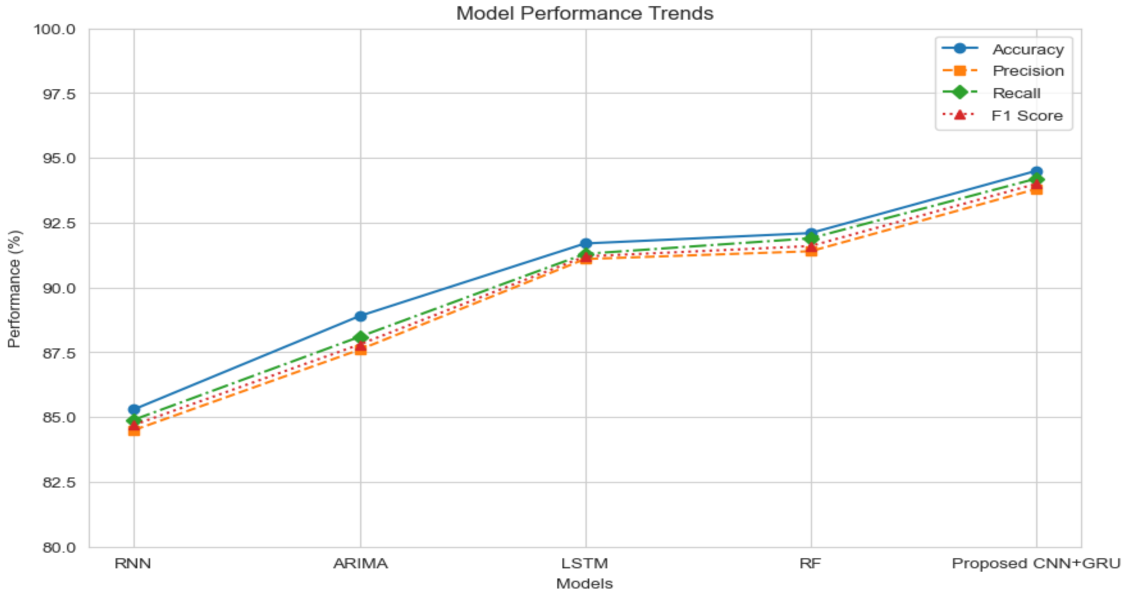

Fig. 6. Evaluation metrics line graph.

TABLE I. EVALUATION OF PROPOSED PERFORMANCE

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
RNN	85.3	84.5	84.9	84.7
ARIMA	88.9	87.6	88.1	87.8
LSTM	91.7	91.1	91.3	91.2
RF	92.1	91.4	91.9	91.6
Proposed CNN+GRU	94.5	93.8	94.2	94.0

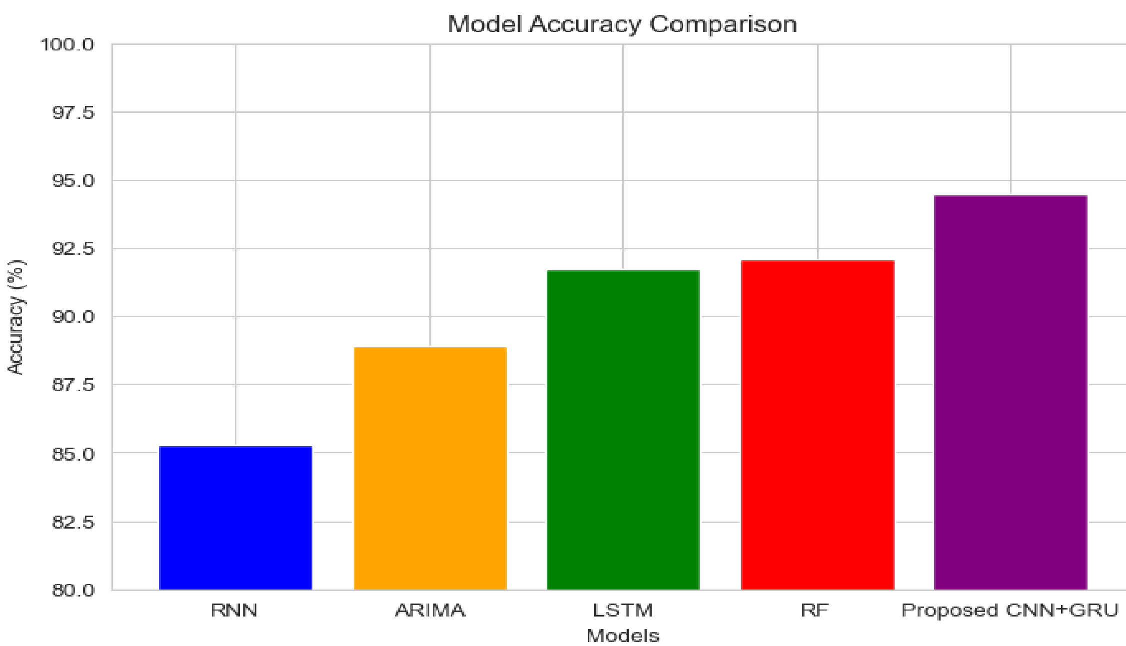

Fig. 7. Performance metrics of existing models with proposed framework.

C. Discussion

The hybrid CNN-GRU model was able to effectively capture the spatial and temporal dynamics of real-world traffic datasets with strong abilities in accurately predicting traffic flow. The GRU layers were able to model temporal dependencies to account for time-based traffic changes, while the CNN layers were capable of detecting spatial traffic features such as road usage trends and congestion hotspots. The integration of the system with IoT sensors, connected vehicles, and real-time surveillance feeds increases its real-time adaptability even more and ensures that the digital twin remains responsive and current at all times. To reduce delays and enhance road safety, this feature supports proactive intervention methods such as rerouting, dynamic signal adjustments, and emergency service prioritization. The model is also highly scalable, as it is necessary for smart cities aiming for homogeneous, citywide deployments, since it can generalize to numerous metropolitan settings with minimal reconfiguration. The simulation capability of the digital twin is cost- and time-saving as it allows authorities to test various traffic conditions. Furthermore, it provides an interactive interface, where policymakers can view the outcomes of traffic measures, which encourages wiser and better-informed decisions on city mobility. Besides solving current inefficiencies, the model sets the stage for further advancements like real-time mechanisms for citizen feedback, environmental sensing, and interfacing with multimodal transportation systems. The integration of CNN-GRU and digital twin is outlined in the discussion as a robust, intelligent, and future-oriented solution that enhances the vision for smart, sustainable urban development. It enhances the efficiency, safety, and convenience of contemporary cities by transforming traffic management from a reactive to a predictive and preventive mode. The data quality and availability is inaccurate and incomplete and can compromise model performance. It has high complexity and computational demand for advanced algorithms. The initial investment and maintenance cost is high. Difficulty to scale twins without performance bottlenecks. Exposing location increases the risk of cyber-attack. Integration and interoperability challenges is difficult due to lack of standards. Some models may not handle complex real world uncertainties. Most digital twin systems lack long term validation in real environment.

VI. Conclusion and Future Works

The research employs hybrid CNN-GRU deep learning model incorporated into a digital twin framework to introduce a robust and new approach to optimizing urban traffic flow. The model effectively integrates the strengths of Gated Recurrent Units (GRUs) for modeling temporal dependency and Convolutional Neural Networks (CNNs) for spatial feature extraction, resulting in an effective spatiotemporal learning system. In comparison to conventional machine learning and time-series forecasting methods, the predictive capabilities of the model were better when it was extensively tested using critical performance indicators, such as accuracy, precision, recall, and F1-score, and trained on actual traffic data. The technology offers city planners and traffic management agencies a powerful tool by detecting significant traffic patterns, including peak hours, congestion points, and flow dynamics at metropolitan intersections. By enabling real-time monitoring, scenario modeling, and proactive decision-making—critical for the development of flexible and sustainable smart city infrastructures—the incorporation of digital twin technology greatly enhances the usefulness of the model.

Future enhancements could integrate multi-source data inputs, such as weather, social event dynamics, and GPS-based mobility data, into the model to increase the model's contextual knowledge and improve forecasting accuracy. Additionally, adding advanced processes like Transformer architecture and attention layers might significantly enhance the model's ability to interpret long-range relations and handle problematic traffic scenarios. In addition, the scalability and utility of the model would be validated through real-world implementation in smart cities. The system would enable automated traffic management, smart rerouting, and adaptive signal regulation through integration with real-time urban infrastructure, enabling intelligent, time-saving, and environmentally sustainable urban mobility solutions. The foundation is created for future traffic systems to be responsive, scalable, predictive, and in compliance with the tenets of smart city living by this research.

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