

Original Article

Deep Learning Empowered Traffic Prediction and Management in Vehicular Networks: Advancing Efficiency and Safety on the Road

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Abstract - Effective traffic management and prediction have been considered the key node in the evolution of modern vehicular networks, whereby great enhancement in road safety, congestion reduction, and overall urban mobility would be afforded. With appropriate traffic predictions, interventions by authorities can be affected in time, with optimization of resources, hence translating to efficient transportation systems. Issues of low predictive accuracy, inability to handle traffic dynamics, and general lack of integration with diverse data sources are also faced by traditional models of traffic prediction. The proposed research work solves the problems described above by putting forward a novel traffic prediction framework, which merges the Adaptive Bilinear Transformer Network, or ABTNet, with the Symbiosis-inspired Multi-Objective Optimizer, or SiMOO. Its architecture is supported by state-of-the-art advanced deep learning techniques with a focus on complex temporal dependencies in traffic data. The SiMOO optimization further enhances the performance of the model with its unique way of symbiotic parameter tuning. The result of such integration will not only improve the accuracy of the predictions but also equip the models to adapt to the fluctuating traffic scenarios, raising higher standards for traffic forecasting. The framework proposed in this study is quite effective and results in a remarkable accuracy of 99% with a low RMSE of 1.65, hence reflecting a far superior performance by the model when compared to the existing machine learning and deep learning approaches. Therefore, the proposed methodology contributes significantly to the development of traffic management systems in vehicular networks, offering good accuracy in real-time traffic predictions that open ways to smarter, responsive urban environments.

Keywords - Vehicular Networks, Traffic Prediction, Traffic Management, Deep Learning, Classification, Road Safety, and Optimization.

1. Introduction

The rapid industrialization has caused a rapid increase in the population residing in metropolitan areas; this is a process that is still changing the face of cities around the world. The word traffic [1, 2], in its simplest definition, refers to the flow of automobiles along a network of roads, monitored by rules and regulations that are supposed to guide their conduct and make sure such movement is both safe and efficient. By definition, therefore, traffic is much more comprehensive than merely the presence of moving vehicles-it involves the dynamic interplay of driver, vehicle, and infrastructure [3] all

playing in relation within the context of a regulated system to order the roads. This, therefore, means that traffic can also be understood as the volume or number of vehicles circulating in a given area during a certain time. Once the traffic has been kept within a certain limit, vehicles may keep moving and thereby maintain a regular flow that assists in a predictable travel time and has less environmental impact. This means that where traffic flow exceeds the capacity of a given road, say during peak hours or highly populated areas of towns, congestion is likely to emerge. Thus, congestion entails a great reduction in the speed of travel, which means longer dwelling



times [4, 5]. For city-dwellers of medium to big cities, traffic congestion becomes a normal feature of everyday life, resulting from pressures placed by population density and high vehicle ownership on the road infrastructure. The more automobiles enter the road network, the more it can carry; it crawls sometimes and stacks up entirely into a gridlock. Traffic congestion is a great concern in medium- to large-sized cities due to population and vehicle growth. Studies [6, 7] discuss urban traffic issues and how traffic networks reach capacity when the traffic demand exceeds the capacity of the network, resulting in severe traffic congestion and traffic snarls. This affects travel time as well as the stress and productivity of travelers. Needless to say, that is not only an inconvenience. The loss of time is perhaps the most tangible and immediate of those effects, leaving commuters having to spend hours in crawl-around traffic with little but lengthy minutes to pass the time. Such lost time ripples further into being a factor in affecting productivity and thus builds stress and frustration in driving behaviors among drivers, which fuels road rage and dangerous behavior.

The inefficiency of stop-and-go traffic means an obvious rise in fuel consumption. Since cars are often left idling or braking and accelerating frequently, consumption is more than in free-flowing conditions. Stop-and-go traffic also results in more fuel consumption. Prior studies [8-10] provide empirical and simulation evidence that idling and stop-and-go traffic result in greater fuel use and emissions for vehicles, compared to vehicles in free-flow traffic. Moreover, people migrate into cities in pursuit of better economic and living opportunities; hence, urban infrastructure is stretched to breaking point. These are the results of rapid urbanization and are dramatically reflected in vehicular traffic congestion. An ever-increasing population presupposes a manifold increase in the number of vehicles on the road, hence an unruly traffic flow that is highly detrimental to orderly movement. Research [11, 12] describe the relationship between population growth, urbanization, and the increase in the number of motor vehicles in a city, and the effect of these on increasing traffic demand and degrading traffic in urban areas. Delays and frustration for commuters are wrought by congestion, besides the waste of time that could be employed in some other beneficial pursuit. Matters are made worse by the fact that many live in suburbs or peripherals and have to commute each day to the central business district to work. In short, traffic congestion is just a reflection of the imbalance between the demand for vehicles and road capacity. Whenever there is a need for more vehicles than what the infrastructural capacity can absorb, then the system begins to break down by slowing down the speed, increasing travel times, and all the unwanted ramifications on environmental and social perspectives. Congestion is a case of supply and demand imbalance. Several studies [13-15] use traffic flow theories to model this and demonstrate how it leads to higher travel times, environmental degradation, and a reduction in urban amenity. With the rise in cities and the vehicle ownership rates, particularly in these rapidly growing

regions, flow management in traffic becomes an important facet to be managed. Proper public transport, along with innovative solutions for traffic management with policies for reducing dependency on private vehicles, will help India brave this challenge. There are a plethora of policy and infrastructure-based measures to address these problems. Study [16] refers to sustainable urban transport policies aimed at enhancing public transport and other initiatives to reduce the car culture, particularly in developing countries like India. Only by understanding how cities get congested can their standards of living be increased and the degradation in the environment begin to improve. Ultimately, cities can only build a more sustainable and efficient urban transport network.

Congestion is a Hydra of many heads and brings with it far more than delay and inactivity. Unquestionably, lost hours wasted sitting in traffic are much clearer; they reach much further into the fabric of living in a city. Traffic congestion also leads to uncertain travel times and affects services. Research works [17, 18] emphasize the uncertainty of traffic flow and its effect on traffic reliability, and study [19] indicates that traffic congestion has a negative impact on the efficiency of service vehicles, implying the need for traffic control measures. The serious problems for commuters are their difficulties in predicting how long it will take to get to their destination; variability in traffic has something unpredictable about it. This leads to frustration and inefficiency because people can no longer plan for their daily routines without some form of interruption in personal as well as professional commitments. Though annoyed at this delay, the impact of congestion on health is becoming increasingly a cause for concern. Since they last for long hours spent in cities, emissions from traffic lead to the concentration of harmful pollutants in the air. These include carbon monoxide, nitrogen oxides, and particulate matter. They contribute to respiratory problems, cardiovascular diseases, and, in general, all decline in public health. More to that, long commutes are stressful and the negative effects emanating from pollution caused by air increase the poisoning effects on city dwellers, thus lessening the quality of life. The other critical issue associated with road congestion is the waste of fuel. Cars that are halted by repetitive stop-and-go movements or held stationary for long periods use so much more fuel than they would have used if they had a smooth drive. Apart from the extra money spent by the drivers, it also creates extra carbon emissions, hence more injurious implications of urbanization on the environment. It then chugs into a vicious cycle of wasted fuel and added emissions to deteriorate air quality and fuel global warming, in turn, festering the public health system in general. Added economic cost, through fuel waste from braking and acceleration in congested traffic, results in faster wear and tear on the vehicle. Perhaps one of the worst secondary effects of traffic congestion is on emergency response services. The worst part is that with traffic congestion, an ambulance, fire truck, or police car becomes stranded in a traffic jam, which may prove fatal at times. Such incidents lead to severe losses

in situations where minutes can turn out to be life-or property-threatening as they do in critical medical emergencies or fire outbreaks. This requires cities to engage with the challenge of low emergency response times resulting from congestion in cities as part and parcel of their more general strategy on traffic management [19]. To date, most cities around the world have adopted forms of traffic management in an effort to reduce congestion levels in the future. For example, there is a car pooling initiative, where car users are encouraged to share the available seats in their cars; this will consequently result in fewer cars on the roads. This therefore reduces congestion and reduces fuel consumption, as well as emissions. To control congestion, some cities opt for smart traffic management. Studies [20, 21] evaluate strategies such as carpooling and congestion charging, which reduce traffic, fuel, and emissions. There have been cities with different types of congestion charges; for instance, there is a charge imposed on drivers who wish to gain access to particular zones, mainly city centers.

1.1. Problem Statement

The high rate of industrialization and the growth in urbanization have only contributed to the congestion in the traffic, which has resulted in the revelation of the weak and inefficient traditional traffic systems that apply the use of fixed rules and minimal historical information. These conventional tools do not quantify the complexity and rapid dynamics of modern traffic, resulting in inaccurate predictions, the failure to manage the timing of the signals, the waste of fuel, and the growth of pollution. The literature available is more or less based on anecdotal nature, non-scalable models, or prediction models; there is an actual gap in the research in the field of real-time, intelligent, and integrated traffic management.

It is filled by the proposed work that suggests a deep learning-based system, capable of learning full hidden spatiotemporal patterns, capable of predicting congestion in a reliable and optimal way, as well as dynamically managing traffic. Unlike the previous research, the novelty of the current research is that it combines prediction and the control of the adaptive signals to improve mobility, decrease emissions, and augment emergency assistance.

This is a more scalable and powerful solution to the growing urban traffic issues with the combined AI-driven solution. The proposed project can enhance the mobility of the urban areas greatly by enhancing the prediction of congestion and smart optimization of the traffic flow. The artificial intelligence support of smart cities projects on a demand basis will help minimize the delays, fuel consumption, and, more importantly, the level of emissions. The efficiency of responding to emergencies and overall road safety will also be improved because of the improvement of route guidance and adaptive signal control. Even better, the model is scaled to the point of being compatible even in large urban chains and

providing the city administrators with an efficient source of sustainable and information-based control over road traffic.

1.2. Research Gap

The research gaps that necessitate further studies on the extant improvements in traffic prediction and management studies have also been established. Whereas machine learning and deep learning approaches have been applied in conducting traditional methods of traffic forecast, little research has been conducted that employs the techniques in taking advantage of real-time multi-source data, such as CV, social situation, or dynamic road condition, which is a critical condition to successful traffic forecasting. Most of the existing techniques rely solely on the contribution of point-based traffic information, which is not very strong and is not very rich in space to explain the interconnectedness and urban traffic spatial richness. Although some deep learning models, such as LSTMs, have shown enormous potential, they are never used due to the high cost of computation and low scalability of the implementation by deployment in large metropolitan traffic systems.

In addition, the ensemble-based prediction model is not a well-examined field, but has the prospect to combine the benefits of different models and, in the process, enhance the performance under different traffic situations. The other clearly sidelined aspect is that of the role of vehicular social networks and user behavior, particularly in regard to vehicular edge computing of information and in traffic optimization. Many of them have also neglected the environmental view of emission levels and the relationship between the traffic flow and the big picture of the city planning strategy. Such gaps will be filled in to assist in developing improved predictive ability in traffic to develop smarter and more effective solutions to the problem of urban mobility, which are sustainable.

1.3. Objectives of the Study

The major research objectives of this paper are as follows:

- The focus of this paper is to come up with an elaborate traffic prediction framework that synthesizes the Adaptive Bilinear Transformer Network (ABTNet) and Symbiosis-inspired Multi-Objective Optimizer (SiMOO) to boost the predictive density and optimize the responsiveness of the framework based on dynamic traffic.
- The goal is to provide a methodological comparison between the newly developed ABTNet and SiMOO methodologies relative to existing ML and DL techniques, with an emphasis on four measurable performance parameters, which are precision, recall, F1-score, and accuracy.
- This paper aims to enhance the previously suggested model to fit realistic vehicular networks better in order to improve the efficiency of traffic management and, consequently, urban mobility.

- Also, this study is to demonstrate the effectiveness of employing the proposed framework and its comparative as well as visualization analysis and outcomes with and/or versus other tools and solutions, which may be beneficial in the case of smart city traffic prediction and management.

1.4. Organization

The paper is divided into four significant sections to provide an overview of traffic prediction and management through deep learning models. Section 2 deals with the literature review on traffic management techniques within vehicular networks by pinpointing the challenges and gaps of existing systems and ways to explore recent advancements in intelligent traffic control through machine learning and deep learning approaches. Section 3 will describe the proposed methodology that indicates the models, methods, algorithms, and architectures used for the models in traffic prediction, along with their data preprocessing and training processes. Discussions for results are to be covered within Section 4, thereby including an elaborate description of how the proposed model has a performance in terms of performance in comparison with existing approaches. This paper concludes with a few of the major contributions and a reflection on the consequences of the findings in Section 5.

2. Literature Review

Rani and Sharma [22] examined the traffic analysis of smart cities using the Decision Tree (DT), Random Forest (RF), Extra Tree (ET), and the XGBoost model. They demonstrate that the performance of the detection process in terms of accuracy and minimum cost of computation is greatly improved once the process is integrated with feature selection. In the given paper, it is also demonstrated that machine learning models of tree-based learning may be quite effective when the relevant features are selected prior to, i.e., feature-based optimization plays an important role in predicting vehicular traffic.

Khan et al. [23] have also performed a detailed examination of the short-term traffic forecasting methods and a detailed focus on the LSTM-based deep learning models. In contrast to the previous reviews, which only give superficial reviews, the paper will give a narrow analysis of the variants of LSTM that have been developed in recent years. The authors dissect the models depending on the amalgamation of LSTM networks with preprocessing and feature engineering schemes, providing a discourse as to the reasons why it is good, bad, or inapplicable in different traffic situations. This is a narrow approach that provides additional value to the survey for the researchers who are interested in having expert short-term forecasting models.

Amiri et al. [24] proposed an ensemble-based approach to enhancing traffic prediction in a VANET environment. Their

model combines LightGBM and Boruta to select features quite well, that is, only the actually informative features are forwarded to the prediction layer. The authors have developed a stacked learning model, which is referred to as STK-EBM, where primary learners, which are RF, KNN, and XGBoost, are optimized by a meta-learner, which is also Logistic Regression. Experimental results reveal that, using such a stacking scheme, the accuracy of classification is much better, and it can be extended to a more complex scenario involving VANET traffic, compared to the traditional machine learning algorithms.

ALMahadin et al. [25] proposed a deep learning model, using GRU architecture to identify unusual traffic patterns in the VANETs, focusing on zero-day unknown cyber threats and DoS attacks. Their work stresses the importance of network integrity protection, especially in multimedia-driven applications within vehicular use cases. Based on the potential of GRU in capturing long-term dependencies, the proposed framework will be more reliable in anomaly detection to provide enhanced protection and threat awareness for vehicular communication systems.

Recently, Zheng et al. [26] presented a comprehensive review of hybrid deep learning models proposed for traffic prediction. Their contribution classifies the feature extraction mechanisms into a taxonomy and discusses architectural components for several hybrid methods. Through a comparison of ten representative models, this article outlines a structured understanding of design choices and performance behaviors in order to help researchers realize effective hybrid configurations for traffic forecasting tasks.

Mittal et al. [27] proposed a model of traffic density prediction that was developed on a deep learning system to make traffic lights control effective. The authors classified vehicles in six categories using the datasets that they had acquired using FLIR, KITTI, and MB7500. To reduce the imbalance issue in classes, they applied data augmentation and the ensemble mode of Faster R-CNN and SSD. This provided an impressive mAP of 94% when used on FLIR thermal images, which is significantly better when compared to the individual SSD and Faster R-CNN models. The findings justify the benefits of combining detection structures in boosting generalization in any imaging.

Ghandri et al. [28] proposed a proactive resource allocation mechanism that handles Variable Bit-Rate (VBR) traffic in MBSFN regions. Their approach dynamically readjusts sub-frames based on predicted fluctuations in traffic load with the idea of attaining maximum system utility by striking the best balance between fairness, throughput, and resource efficiency. This periodic adjustment in MBSFN resources ensures improved adaptability to rapid changes in VBR demands.

Wang et al. [29] tackled the problem of congestion mitigation using an enhanced method for traffic flow prediction. The authors consider that single-point forecasting methods cannot capture the spatial context and therefore cannot make effective short-term predictions in a complex network of roads. To address this issue, they incorporate historical data with topological information related to the road network. Experimental evaluations by the authors using real-world datasets demonstrate that their mixed-method approach achieves much higher accuracy compared to conventional machine learning models, thus making the method a good candidate for real-time urban traffic forecasting. Aung et al. [30] presented a social-aware vehicular edge computing architecture for efficient content distribution. In their scheme, certain vehicles were selected as edge servers to store and distribute popular content. The architecture of the system consists of a social-aware graph-pruning algorithm to find the optimal content providers and a traffic-aware recommendation strategy based on graph embeddings, namely vehicle2vec. Considering both social and traffic dynamics,

this model has provided context-aware content delivery, and it is thus considered a promising solution to bandwidth and latency issues in vehicular networks.

Khadka et al. [31] proposed a method to estimate regional link volumes by using Connected Vehicle data in conjunction with a Deep Neural Network model. The authors create training pairs by matching the link volumes with CV counts at corresponding locations. A DNN model yields higher accuracy when compared to linear regression and random forest models. By applying the model to large-scale CV datasets, the study shows the potential to create more comprehensive and data-driven traffic volume predictions across diverse regions. Table 1 compares with other existing traffic prediction and vehicular network analytics methods. It is obvious that these approaches are either not efficient or effective in terms of accuracy, robustness, or adaptability, which motivates the proposed ABTNet.

Table 1. Comparison of existing studies on traffic prediction and vehicular network analytics

Authors	Methods / Models Used	Performance Metrics / Findings
Rani & Sharma [22]	Decision Tree (DT), Random Forest (RF), Extra Tree (ET), XGBoost with ensemble learning	Higher detection accuracy and lower computational cost; feature-selected models outperformed non-feature-selected ones
Khan et al. [23]	Systematic review of LSTM-based short-term forecasting models	Comparative insights into LSTM-based models highlighted applicability across multiple short-term forecasting scenarios
Amiri et al. [24]	Stacking Ensemble Learning with Booster Model (STK-EBM), Boruta + LightGBM for feature selection; RF, KNN, XGBoost as base learners; Logistic Regression meta-learner	Achieved higher accuracy than baseline ML models; the ensemble method significantly boosted classification performance.
ALMahadin et al. [25]	GRU-based deep learning model for anomaly detection	Improved anomaly detection capability and enhanced identification of suspicious traffic behavior
Zheng et al. [26]	Hybrid deep learning models: taxonomy-based comparative review	Comparative performance analysis across hybrid architectures, offering insights into model suitability
Mittal et al. [27]	CNN-based vehicle detection; Faster R-CNN + SSD ensemble; datasets: FLIR, KITTI, MB7500	Achieved 94% mAP on FLIR thermal data, outperforming SSD by 34% and Faster R-CNN by 6%
Ghandri et al. [28]	Proactive resource allocation using DL-based VBR traffic prediction for MBSFN	Improved utility and adaptability under fluctuating VBR traffic conditions
Wang et al. [29]	Mixed prediction model integrating historical data + road-network structural information	Demonstrated significantly better accuracy than traditional ML models using real-world datasets
Aung et al. [30]	Social-aware vehicular edge computing; social-graph pruning; traffic-aware content recommendation; vehicle2vec embeddings	Enhanced delivery efficiency and improved relevance of recommended content
Khadka et al. [31]	Deep Neural Network (DNN) for estimating link volumes using Connected-Vehicle (CV) data	DNN outperformed LR and RF in estimation accuracy; enabled holistic data-driven regional traffic volume prediction

2.1 . Hypothesis of the Present Study

- H1: ABTNet significantly outperforms the state-of-the-art deep learning architectures by offering an improved modeling for nonlinear temporal-spatial traffic patterns.
- H2: The SiMOO outperforms other parameter optimization techniques and converges faster with higher predictive accuracy than traditional optimizers like Adam or RMSProp.
- H3: The ABTNet–SiMOO combination yields statistically better performances in the various evaluation metrics considered, namely MAE, RMSE, R², Precision, Recall, and F1-score, compared to state-of-the-art contemporary traffic prediction models.
- H4: The proposed model generalizes effectively in heterogeneous traffic environments and shows stable performance in various conditions, including peak hours, irregular congestion, or lack of sensor data.
- H5: The real-time deployment of the ABTNet–SiMOO framework enhances the efficiency in traffic management while enabling more accurate and timely predictions for vehicular networks.

3. Proposed Methodology

The proposed work presents a new framework for traffic prediction, addressing the limitations of the available models that fail to capture the highly dynamic and complex nature of modern vehicular networks. This model learns long-range dependencies and adapts to fast-changing traffic patterns effectively by integrating the Adaptive Bilinear Transformer Network with a symbiosis-inspired multi-objective optimizer. ABTNet's bilinear attention can model richer interactions among key variables like speed, density, and flow, while SiMOO dynamically adjusts learning rates for better convergence and prevention from overfitting. This synergy not only improves prediction accuracy but also ensures scalability and suitability for real-time deployment in large urban networks.

In this regard, the proposed ABTNet, which can lead to the confluence of deep-learning techniques with the creation of a transformer architecture to enhance the possibilities of prediction related to the auto-traffic. The optimization of learning rates in this model is done by the assistance of symbiosis-inspired multi-objective optimizer, and, consequently, makes it possible to predict in this way with a greater degree of accuracy as it turns into a dynamically changing one according to the changing patterns. The paper integrates the advantages of transformer models and bilinear attention mechanisms, which produce a high level of prediction accuracy and provide the strength of traffic forecasts in different operational conditions. The innovation of the methodology suggested herein lies in its distinctive combination of the diversified data sources and the latest computational methods in the creation of the population traffic flow predictions that will be much closer to the truth than

those observed to date. ABTNet can identify intricate interdependences and interactions among vehicles by relying on historical traffic statistics as well as information in the context of vehicular networks, and can therefore assist in making superior forecasts of the traffic conditions. This fits the nature of vehicular networks, wherein the interaction between different streams of traffic and real-time data input plays a very important role in determining the complete dynamics of traffic flow. The current model focuses on structured work, starting first with the preprocessing of data in order to preserve the quality and relevance of input data sets and then using our ABTNet framework, which will include feature extraction, attention mechanisms, and learning rate optimization in order for dynamic adaptation to changing traffic conditions. The proposed traffic prediction and management system is depicted in Figure 1, which illustrates the process in which the traffic data is collected, pre-processed, features are extracted, optimized (SiMOO), and predicted (ABTNet). Clearly, the introduction of the optimization and deep learning blocks to manage traffic variations improves the accuracy and adaptability of the traffic prediction system.

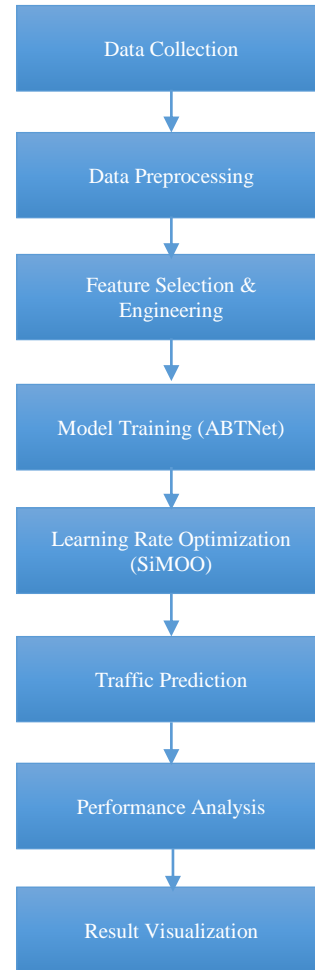


Fig. 1 Overall flow of the proposed traffic prediction and management system

The proposed methodology uses a structured and adaptive workflow for the prediction of traffic conditions with high accuracy in vehicular networks. The process goes through data collection, which includes heterogeneous traffic data such as the speeds, densities, and flows of moving vehicles, collected from IoV sensors and monitoring systems. Intensive preprocessing involves missing values, removing noise, normalizing features, and preparing the data for reliable learning. The second step is the feature selection and engineering to determine meaningful spatiotemporal features that may be the most suitable descriptions of dynamic traffic behavior. The obtained refined features will be fed into the ABTNet model that obtains bilinear attention and transformer-based encoding to extract long-range dependency and complex interactions among traffic variables. SiMoO optimizer modulates the learning rate in model training to enhance the convergence, overfitting, and stability to varying traffic conditions. With optimization, the modeled traffic prediction will generate precise forecasts within the short-term and long-term periods. The detailed performance analysis is conducted and represented using a visualization, which is intuitive to obtain results in a presentable format that makes it real-time applicable in the smart city traffic management systems.

3.1. Adaptive Bilinear Transformer Network (ABTNet) for Traffic Prediction in Vehicular Networks

ABTNet is designed as an advanced traffic prediction model for vehicular networks in smart cities. Nowadays, the diversified and more complex vehicular traffic patterns and the explosion of data produced from IoV networks have contributed to inefficiency and lower accuracy for conventional techniques in recent years. In order to solve this problem, ABTNet extends the Transformer model by incorporating bilinear transformation and adaptive multihead mechanisms. This yields a simple yet effective and easy-to-scale approach for traffic prediction tasks. This technique has been adopted in this work because it is better suited to model the long-range dependencies that exist in vehicular network data, as opposed to classic deep learning models such as RNNs or CNNs, which may suffer from temporal dependencies and highly dynamic traffic conditions.

At the heart of ABTNet lies a bilinear attention mechanism for capturing complex dependencies among various traffic variables at the level of vehicle density, speed, and flow. Traditional mechanisms of attention focus on learning the interactions between different tokens or data points, while bilinear attention enables the model to take into consideration pairwise interactions among all elements in the traffic data, thus enabling a much finer and dynamic perception of traffic flow. The adaptive component comes along with the dynamic variations of the heads of attention in accordance with the real-time flow of traffic. This allows the model to be trained on what and what details of the information would be given more weight at any one particular

time, therefore giving better predictions of the dynamic traffic environment. This is so flexible that the model is resilient enough to withstand immediate changes in the pattern of the traffic flow- an accident, the shutting down of some roads, rush time congestion.

ABTNet is also special and more efficient compared to other prediction mechanisms of traffic because it manages to combine the strengths of bilinear transformation with the scaling self-attention mechanism of Transformers. Bilinear transformations by themselves are able to capture the relations of different variables way better than state-of-the-art methods, thus making the model effective in modeling complex relationships in a traffic network, which other techniques might fail to notice. The inherent capability of the Transformer architecture for handling sequence-to-sequence data with much efficiency enables ABTNet to predict multi-road segment traffic flow that is interconnected in the network. Such spatiotemporal dependency modeling is crucial in vehicular networks, where traffic flow in one region directly influences other areas. ABTNet heavily relies on the self-attention mechanism that still reduces the computational complexities common in recurrent models, hence making it suitable for large-scale real-time traffic prediction tasks.

The originality of ABTNet is the adaptive bilinear attention mechanism, which may capture in a dynamic way intricate interdependencies learned from the diverse features of traffic. While the current models work well, with simpler Neural Networks and other more classical algorithms, such as decision trees and random forests that usually perform rather poorly due to their simple structure, which restricts them from capturing complex relations in traffic data, this bilinear layer is in place to ensure that the model considers all possible interactions between the traffic variables that are to be estimated.

Besides, the model follows an architecture of stacked Transformers in such a way that each later refines the prediction based on a deeper insight into the dynamics of traffic, hence coming out with highly accurate predictions for multiple time steps. Another novelty of ABTNet is the integration with real-time data from vehicular networks. With this information in real time, the model dynamically readjusts its parameters and mechanisms of attention to adapt to changes that may pop up in real time in traffic flow. In Figure 2, the proposed scalable and modular design is suitable for smart cities. It demonstrates efficient real-time data stream management, which allows real-time traffic predictions.

On aspects of accuracy, ABTNet fares well with the incorporation of multiple heads of attention, which give focus to different aspects simultaneously in the traffic data. Each attention head will learn to attend to different aspects of the input data, such as congestion of roads, traffic flow, or speed of vehicles, so that the model can draw upon many various

types of information that could impact the pattern of the flow. These are then combined using the bilinear attention mechanism to provide more accurate and reliable predictions by the model. The ABTNet bilinear and adaptive attention

mechanisms have a holistic view of the traffic; this, in turn, enhances the network to realize high-accuracy forecasts of both short-term and long-term traffic even in the presence of unforeseen events such as accidents or unexpected congestion.

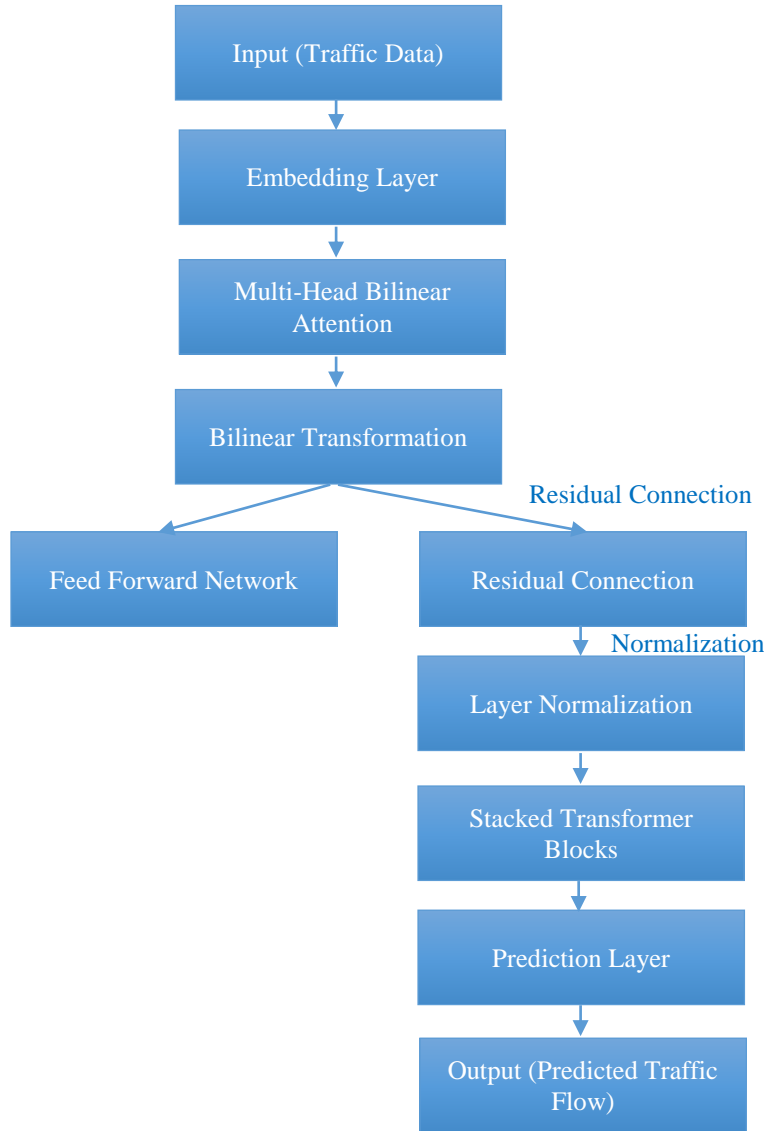


Fig. 2 Architecture model of the proposed ABTNet

Another huge distinct feature, as far as ABTNet is concerned, is scalability and flexibility. Unlike the traditional models, which might fail when having large networks, ABTNet is hardly influenced by the huge loss in performance when large datasets of the urban vehicular networks are considered. The unspoken premise of utilizing efficiency in long sequences of Transformers will imply the suitability of ABTNet to large road networks when the flow of traffic should be projected across several roads simultaneously. Its scalability makes it a convenient tool in practice when it is applied in smart cities, where the data collection of traffic is multi-faceted: IoT sensors, cameras, and GPS devices.

ABTNet-Attention-based Traffic Prediction Network represents a leap forward in state-of-the-art techniques for vehicular networks' traffic prediction. The novelty of ABTNet is due to adaptive multi-head attention and bilinear transformations, thus enabling precise modeling of complex patterns of traffic flows. It does this while adapting to real-time data both in terms of accuracy and scalability. ABTNet is revolutionary from an aptitude perspective in terms of managing traffic in smart cities for better control measures that reduce congestion, enhance urban mobility through the accurate forecasting of real-time traffic flow.

Initially, the scaled dot product attention mechanism is implemented at first with the parameters of query, key, and value matrices as mathematically described in Equation (1):

$$\text{Attention}(\mathfrak{X}, \mathfrak{Y}, \mathfrak{Z}) = \text{Softmax} \frac{\mathfrak{X}\mathfrak{Y}^{\mathfrak{S}}}{\sqrt{d_s}} \quad (1)$$

Where, $\mathfrak{X}, \mathfrak{Y}, \mathfrak{Z}$ are the query, key, and value matrices, and d_s represents the dimensionality of key vectors. After that, the traffic patterns are captured and integrated with the use of a multi-head attention function. Consequently, the sequence of traffic data is encoded with the positional function as represented in Equations (2) and (3):

$$\mathcal{PE}_{(\mathcal{p}, 2i)} = \sin \frac{\mathcal{p}}{1000^{2i}} \quad (2)$$

$$\mathcal{PE}_{(\mathcal{p}, 2i+1)} = \cos \frac{\mathcal{p}}{1000^{2i/b}} \quad (3)$$

Where, \mathcal{p} represents the position. Then, the transformer's encoded output is obtained with the multihead attention module according to the following model:

$$\mathcal{H}_{\text{enc}} = \text{Layer}_{\text{norm}}(\mathcal{S} + \text{Multi}_{\text{head}}(\mathfrak{X}, \mathfrak{Y}, \mathfrak{Z})) \quad (4)$$

Where, \mathcal{H}_{enc} is the encoded output. Moreover, the energy function is computed with the component of DBN as shown below:

$$\mathbb{E}(\mathbf{v}, \mathbf{h}) = -\sum_i v_i b_i - \sum_j h_j \xi_j - \sum_{i,j} v_i h_j w_{ij} \quad (5)$$

Where $\mathbb{E}(\cdot)$ indicates the energy function, \mathbf{v}, \mathbf{h} are the visible and hidden layers, w_{ij} is the weight value, and b_i denotes the bias value. Consequently, the probability function is estimated for both the visible and hidden units according to Equations (6) and (7):

$$\mathbb{P}(v_i = 1 | \mathbf{h}) = \varphi \sum_j h_j w_{ij} + b_i \quad (6)$$

$$\mathbb{P}(h_i = 1 | \mathbf{v}) = \varphi \sum_j v_j w_{ij} + \xi_j \quad (7)$$

Where φ represents the sigmoid activation function, furthermore, the weight update is performed with the contrastive divergence function with the learning rate as shown in Equation (8):

$$\Delta w_{ij} = \partial((v_i h_j)_{\text{data}} - (v_i h_j)_{\text{rec}}) \quad (8)$$

Where ∂ is the learning rate that is optimally estimated using the proposed SiMOO model, $(v_i h_j)_{\text{data}}$ and $(v_i h_j)_{\text{rec}}$ indicates the expectation over the data distribution and the reconstructed distribution. Furthermore, the hidden features extracted from the DBN are passed to the transformer model as represented below:

$$\mathcal{S}_{\text{inp}} = \mathcal{H}_{\text{DBN}} + \mathcal{H}_{\text{enc}} \quad (9)$$

Finally, the traffic prediction is estimated according to the output of the transformer model with the use of a fully connected layer operation as mathematically represented below:

$$\mathbb{T}_{\text{pre}} = \text{Softmax}(\mathbf{w}_{\text{out}} \mathcal{H}_{\text{out}} + \mathbf{b}_{\text{out}}) \quad (10)$$

Where, \mathbb{T}_{pre} indicated the predicted traffic pattern, \mathbf{w}_{out} and \mathbf{b}_{out} are the weight and bias values.

3.2. Symbiosis-inspired Multi-Objective Optimizer (SiMOO)

SiMOO abbreviates a new paradigm in computing the learning rate of the ABTNet model to attain improvement in traffic prediction accuracy over vehicular networks. In all deep learning models, including ABTNet, the learning rate is one of the most important hyperparameters due to the pace it gives for convergence to a solution while optimizing. This is appropriate because an appropriately tuned learning rate will influence much in terms of convergence speed and overall effectiveness in modeling complex patterns within the traffic data. In handling such complex interactions between multiple vehicles and environmental factors, ABTNet must be held back with great caution to avoid a learning rate that might shoot upwards, overshooting the optimal solution, or being too low to be stuck in a poor local minimum. By applying SiMOO for calculating the learning rate, ABTNet enjoys a unique biological symbiosis optimization mechanism where organisms with different natures coexist and support each other to grow and be efficient. This kind of optimization technique can therefore enable ABTNet to adjust the learning rate dynamically based on real-time feedback from the training process; hence, it enables ABTNet to track a much more adaptive learning strategy.

Figure 3 shows the multi-objective optimization of the SiMOO algorithm, where it is observed that the model aims to minimize the prediction error and robustness, as the convergence curve indicates that the objective values converge after a certain number of iterations, and thus the model can achieve good results. The multi-objective nature of SiMOO helps to optimize simultaneously different objectives, such as minimum prediction error along with maximum model robustness. This is of particular relevance for the scenarios on traffic prediction, where fluctuating conditions in the flow and diversified vehicular behaviors may introduce high variability in the data. Maybe the innovation of including SiMOO in the computation of the learning rate for the ABTNet model has the potential for a higher predictive accuracy because of its more responsive learning mechanism. This is considering how easily traffic patterns can fluctuate, and may be substantially different over time and with external influences. In any case, a fixed learning rate would never be able to grasp such dynamics relevantly.

Adaptability imparts to SiMOO the ability to learn at different rates, which at any instant in time adapts to the different complexities that each input data brings. This, in turn, leads to better convergence and hence better-represented traffic conditions. For this reason, it would be said that the traffic forecast of an ABTNet model is highly reliable, precise,

and useful for traffic management and urban planning. In short, the advent of SiMOO is highly expected not only to optimize the learning process but also to improve ABTNet's general efficiency in solving the traffic prediction problem of vehicular networks and thus stands as one of the fantastic developments of the deep learning techniques within this field.

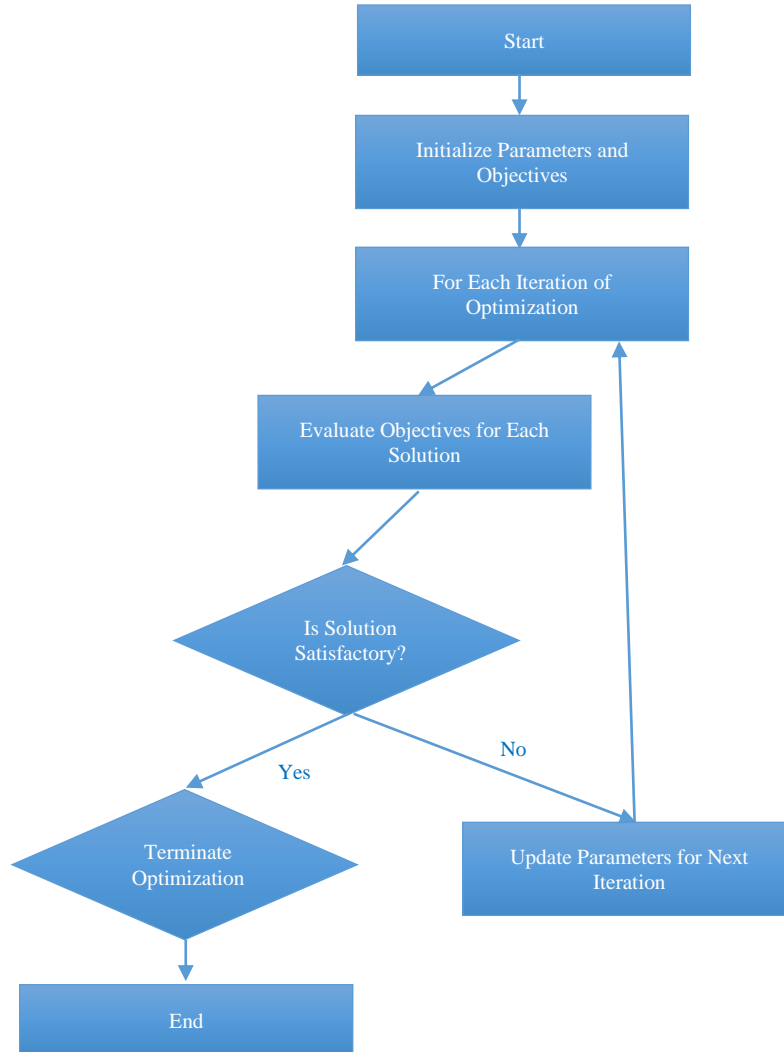


Fig. 3 Flow of the proposed SiMOO algorithm

The flow proceeded with Symbiosis-inspired Multi-Objective Optimizer while calculating the learning rate of ABTNet, which involves model parameter initialization and hyperparameter initialization. Then it describes the initialization of the initially best solution, commonly from the heuristics of the problem or default evaluation at the start of the learning phase. During the training in each epoch, it would consider feature extraction in vehicular network traffic data volume, vehicular network traffic speed, and other vehicular network environmental factors. While obtaining such data into the model, forward propagation through the multiple layers of the designed model is performed using attention mechanisms that help learn dependencies and interactions of traffic

features. On the other hand, SiMOO examines the current assessment of how the model is performing, such as prediction accuracy and loss. This also creates a feedback loop that SiMOO can make regarding the learning rate concerning the performance which has been observed, concerning changes in the training conditions of the model, and thus making the model almost adaptive. When training transpires, all these come into play, and within the SiMOO framework, which closely involves multiobjective optimization, other objectives relating to the learning process are considered. It might be set, for example, to minimize prediction errors at the same time as allowing the possibility of generalization in traffic situations. In this way, this study avoids capturing and becoming

bounded within the basic learning rate range for the ABTNet model and instead allows it to deal with the complexities within input data. Besides this readjustment of learning rates, the model, however, attains a better convergence characteristic and consequently provides a more accurate forecast, because it learns suitable representations of traffic patterns.

This finally makes SiMOO to be presented as an inseparable part and component of the whole training process of ABTNet, and thus it could be said to be a very powerful tool in the efficient traffic prediction of dynamic vehicular networks.

4. Results and Discussion

The obtained results for the proposed ABTNet Adaptive Bilinear Transformer Network and SiMOO Symbiosis-Inspired Multi-Objective Optimizer are deeply analyzed in this section with respect to traffic prediction in vehicular networks. Our findings are based on extensive experimentation conducted on various datasets preprocessed with great care to ensure their appropriateness for model training and evaluation. The main objective is to present the performance of the ABTNet model in performing the prediction of the traffic pattern with the optimized learning rates derived through SiMOO.

A strict evaluation framework has been followed, which regards a number of performance metrics that include MAE, RMSE, and R-squared values to quantify the predictive accuracy of the model. Besides this, we have also made comparative studies with some of the baseline models, such as classical machine learning algorithms and other newer models of deep learning.

The results do not only indicate the high performance of the proposed methodologies but also the strength in different traffic situations and conditions. We proceed to show how all these factors form a considerable part of our framework in which we are bringing ABTNet in SiMoO to further offer higher-performance traffic management systems in present vehicular networks. The work under development relies on the data of traffic prognosis presented by Simulation of Urban Mobility (SUMO) as the source of the necessary data; this is one of the most significant resources, and its set of traffic patterns is very large and diverse, and is required to test the models that are under consideration. In that sense, a well-studied document can document the real traffic situation such that the suggested methodologies can get acquainted with the intricate traffic pattern and behavior in urban traffic systems.

However, the amount of data is enormous, thus providing the model with strength as well as the fact that the predicted traffic model will be correct and reflect the real vehicular networks, and that it can be utilized in developing better traffic control models. The real-world traffic is diverse, and the SUMO dataset [32, 33] helps to seize different traffic situations relevant for the training and evaluation of the designed traffic prediction model.

The inclusion of the SUMO dataset makes it possible for our approach to be applied in traffic management requirements to provide actual traffic network prediction of vehicular traffic in urban areas. The details of the experimental environments in this work, including sample sizes, feature sizes, and training-testing data ratios and parameters, are shown in Table 2. This allows us to verify the validity of the proposed ABTNet model.

Table 2. Summary of dataset characteristics and parameters used in the study

Parameter	Description
Dataset Name	SUMO Traffic Dataset
Dataset Type	Simulation-based synthetic urban vehicular traffic data
Source / References	SUMO environment; referenced in studies [32, 33]
Coverage	Multiple urban traffic scenarios, including peak-hour flow, intersection congestion, heterogeneous vehicle behavior, and mixed-density patterns
Key Features	Timestamp, vehicle ID, speed, lane ID, position, road segment ID, traffic density, flow rate, travel time
Preprocessing Operations	Data cleaning, normalization, missing-value removal, temporal sequence formation, spatial mapping, feature scaling
Input Parameters for Model	Spatiotemporal traffic sequences, vehicle movement features, optimized learning rate, window size, batch size
Output Parameters	Predicted traffic flow, density, speed; MAE, RMSE, and R ² performance metrics
Evaluation Metrics	MAE, RMSE, R-squared (R ²); comparative assessment with baseline ML and DL models
Dataset Strengths	High realism, diverse scenarios, well-suited for modeling dynamic urban traffic patterns.
Application Domains	Intelligent vehicular networks, congestion prediction, adaptive traffic control, smart city traffic management

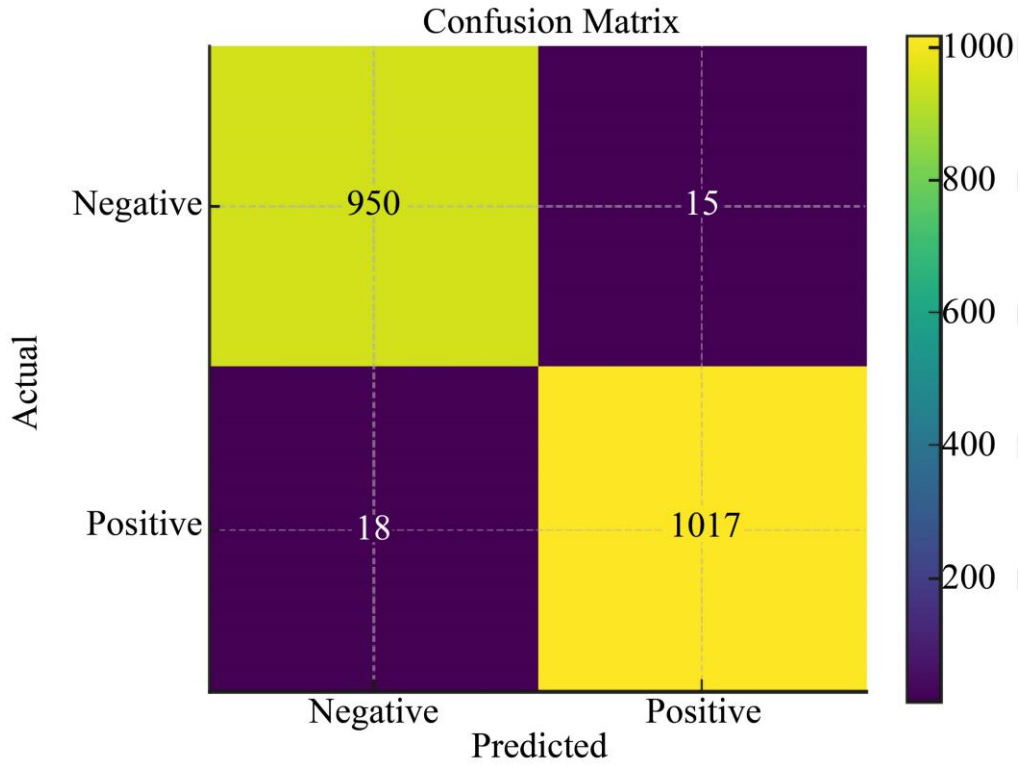


Fig. 4 Confusion Matrix

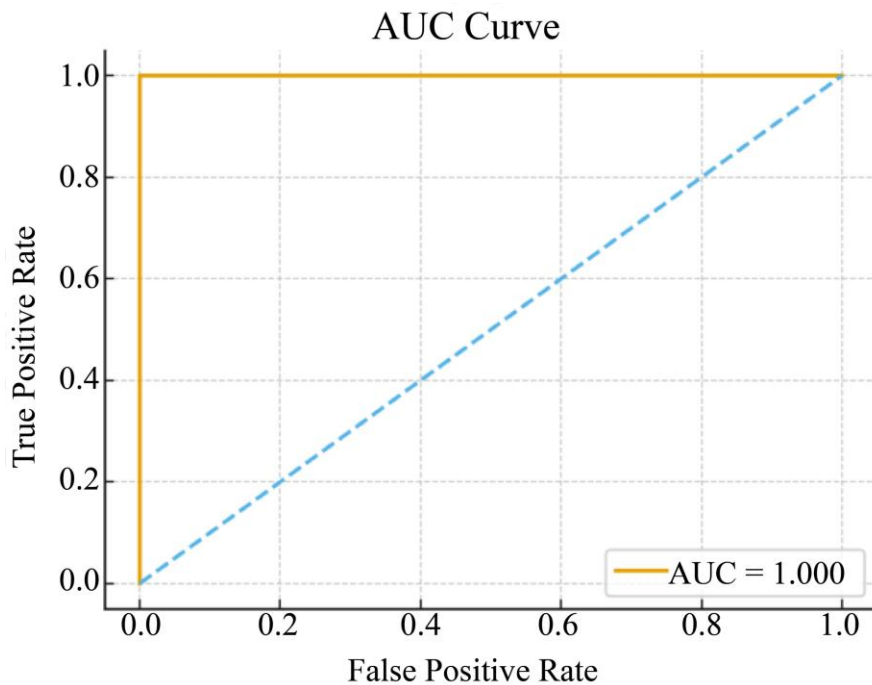


Fig. 5 AUC Curve

The confusion matrix of the proposed ABTNet model demonstrates an exceptionally strong classification capability, showing a very high number of true positives and true negatives with only minimal misclassifications. This is in tune with the reported Precision (98.9%), Recall (98.9%), and F1-

score (99%) that prove the model's reliability in finding both congested and non-congested traffic states. This is further confirmed by the AUC curve of ABTNet, which achieved a very high AUC close to 1.0, showing outstanding separability between positive and negative classes. Compared to other

machine learning and deep learning models, ABTNet has shown a much steeper ROC slope and an extremely low false-positive rate. From Figures 4 and 5, it can be seen that the proposed ABTNet model performs better than other models. In Figure 4, it can be seen that the AUC curve is close to 1.0, which implies good discrimination, and in Figure 5, it can be seen that the model does not have many misclassifications with higher true positive and true negative rates, which implies the stability of the model. It also compares the results of ABTNet with different experimental settings in Table 3 and Figure 6. These results indicate that ABTNet is stable under various experimental settings, with better prediction performance and lower error rate than the baseline models, demonstrating the stability and adaptability of the proposed approach. The proposed ABTNet has been tested for traffic prediction in the different experimental setups it has been compared with some benchmark machine learning models utilizing the SUMO dataset. In fact, the performance measures, including Precision, Recall, F1-score, and Accuracy, clearly represent that the proposed model performed better, and it achieved a Precision of 98.9, a Recall of 98.9, an F1-score of 99, and an Accuracy of 99%. While

others, like Random Forest and Support Vector Machine, respectively incurred Precision (PV) of 94, 92; Accuracy (AC) of 90, and 90.8. However, the utility and value ratio with ABTNet is much higher compared to average Ensemble methods, the one that has the highest scores for standard models, with the accuracy result of 94.1%. This again brings out the fact that the model proposed is helpful in capturing the various flow patterns of traffic and, therefore, arriving at a better forecast to enhance the usefulness of the traffic management systems in an urban setting.

Table 3. Overall comparison with other machine learning-based traffic prediction models using the SUMO dataset

Methods	Precision	Recall	F1-score	Accuracy
RF	94	86	89	90
KNN	94	92	93	93.6
NB	76	79	77	77
DT	91	91	91	91.7
SVM	92	87	89	90.8
MLP	94	90	92	92.5
Ensemble	94	98	95	94.1
Proposed	98.9	98.9	99	99

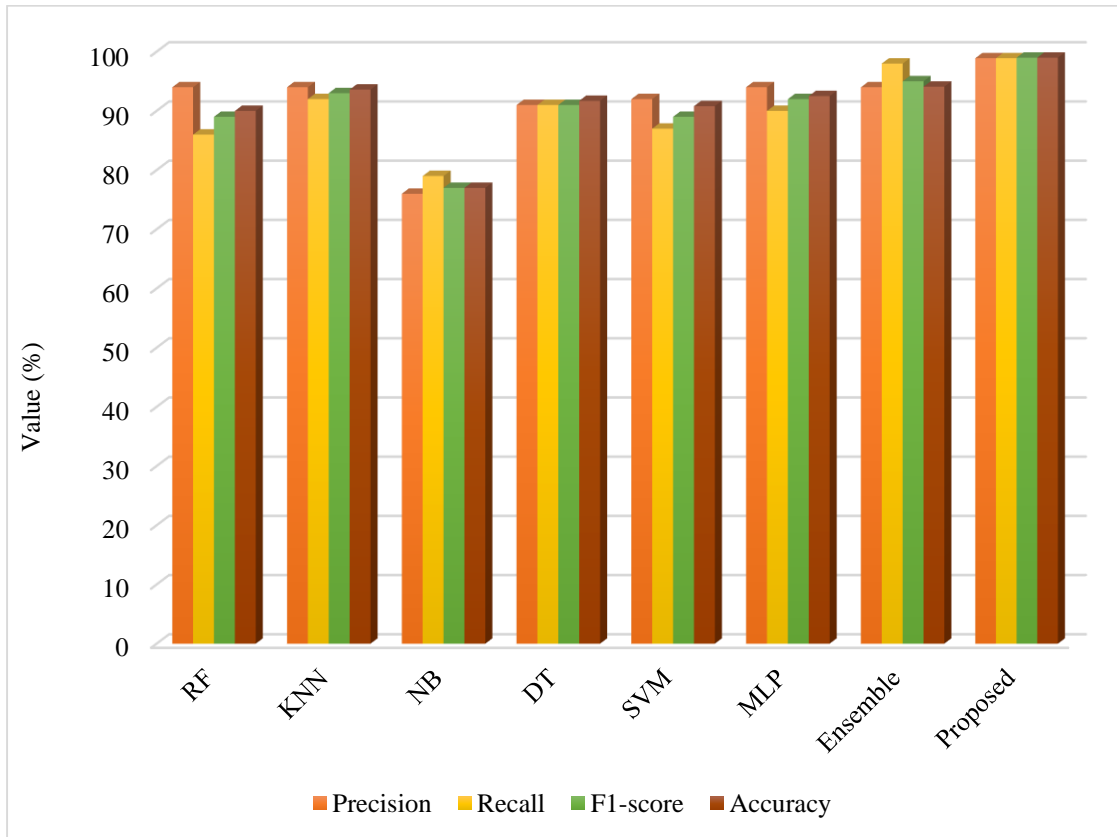


Fig. 6 Comparison with existing machine learning techniques using the SUMO dataset

In the start, comparison is made with the machine learning models only; Table 4 and Figure 7 further enhance the proposed technique by comparing with the recent advanced methodologies. The current proposed model is once

more highlighted; again, it has an FP of 98.8%, its Recall is 98.9%, which is significantly higher than AlertNet and DNN, which recorded 81%, 83% respectively. That proves that the proposed model has an F1-score of 99, showing that the

proposed model has a better ability to sustain a balance between Precision and Recall, an extremely important factor in traffic prediction, where either of the two, the false positive and false negative, can lead to many operational losses. Such a huge difference points to the possibility of ABTNet to deal with the weaknesses of current methodologies and adapt to various traffic conditions. Table 5 and Figure 8 also compare the proposed approach with other recent state-of-the-art models. This indicates that the new model (ABTNet) has better accuracy than other models, showing its capacity to forecast traffic in complex conditions. Furthermore, the rate of

99% proposed with the model is perfect; few other models, like SEMI-GRU, had an accuracy of 83.32%. Indeed, this excellent performance suggests that ABTNet is robust with regard to real-time traffic data streams and demonstrates its compatibility to cope with the problems of vehicular networks. Of course, it will be noticed that each of the Figures gives the massive improvement achieved by ABTNet for the concrete embedding in predicting the traffic accurately in the vehicular networks and, hence, making the justifiable case for implementing it in smart city infrastructure and intelligent transportation systems.

Table 4. Comparison with recent approaches based on precision, recall, and F1-score using the SUMO dataset

Methods	Precision	Recall	F1-score
AlertNet	81	78.56	76.52
DNN	83	68.56	75.58
ANN	80	66.41	74.28
CNN	81.25	68.52	71.26
MCNN	83	81.26	81.23
MCNN-DFS	81	95	80.25
MDNN	81.25	84.23	75.65
NB	76.53	74.28	72.06
J48	79.68	76.54	71.25
RF	82.56	78.64	72.56
Bagging	78.56	77.25	72.06
AdaBoost	65.56	68.53	65.96
SEMI-GRU	93.8	78.36	85.62
Proposed	98.8	98.9	99

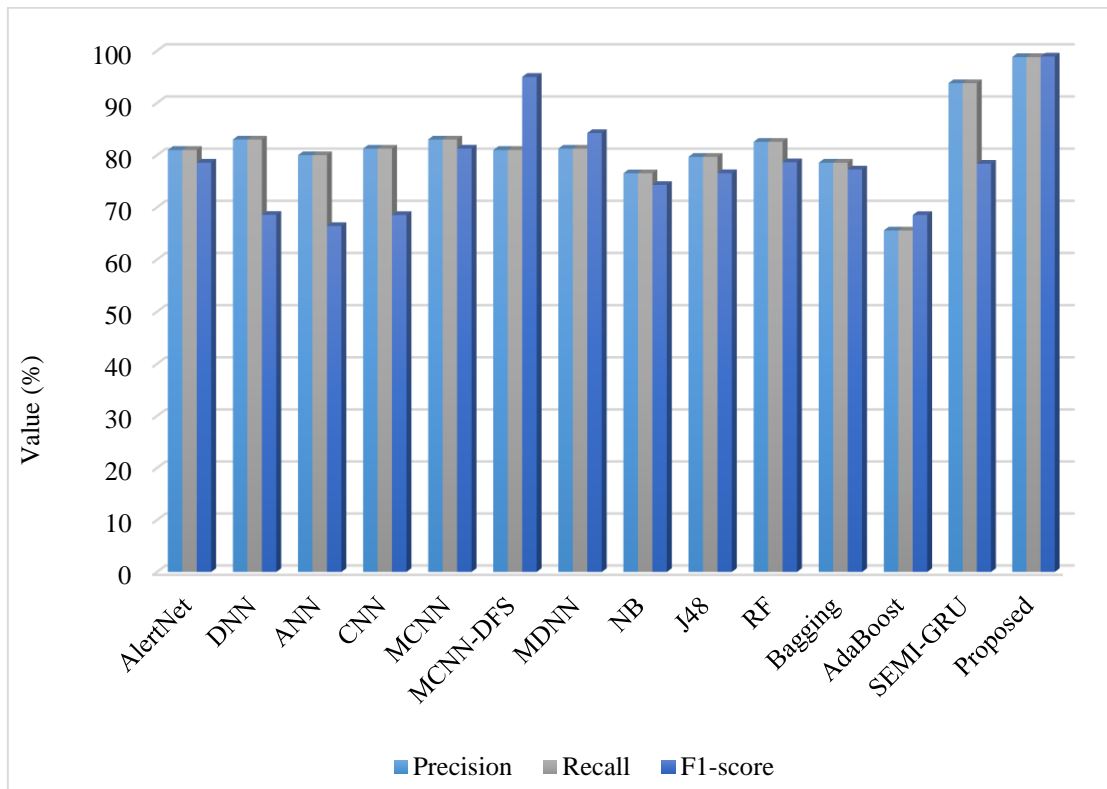


Fig. 7 Comparison with recent learning techniques using the SUMO dataset

Table 5. Comparison with recent approaches based on accuracy using the SUMO dataset

Methods	Accuracy
AlertNet	78.5
DNN	79.1
ANN	79.9
CNN	79.4
MCNN	81
MCNN-DFS	81.4
MDNN	77.5
NB	72.45
J48	74.9
RF	76.45
Bagging	74.84
AdaBoost	66.5
SEMI-GRU	83.32
Proposed	99

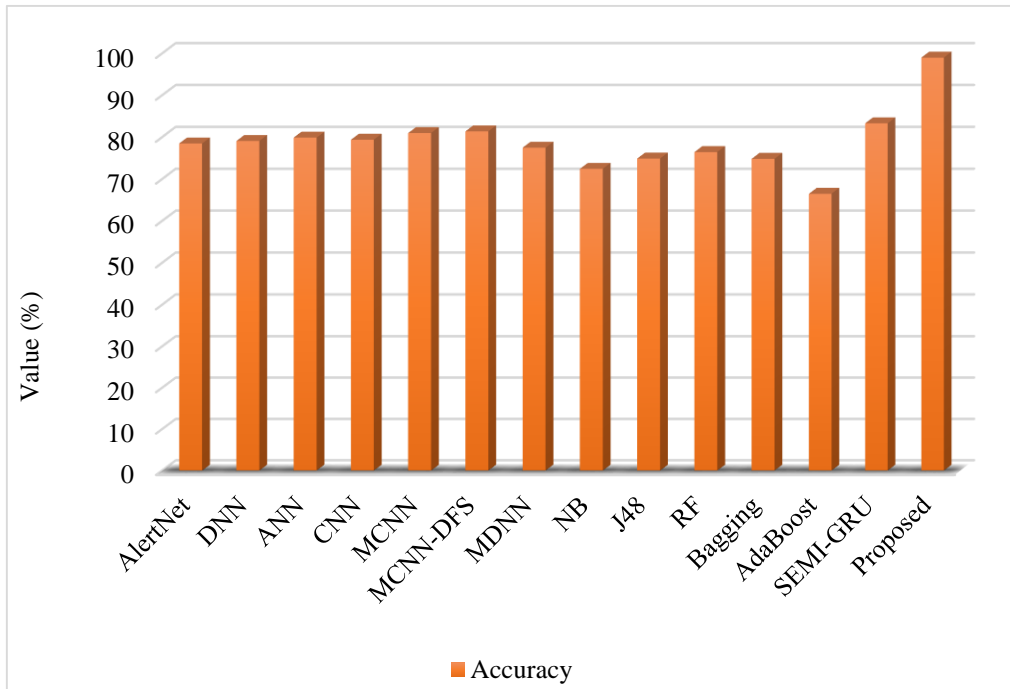


Fig 8. Comparison with recent learning techniques using the SUMO dataset based on accuracy

Table 6. Comparison with other deep learning architectures based on RMSE

Methods	RMSE
BiLSTM-WA	2.67
LSTM	9.37
ITPM	5.67
BiLSTM	8.36
CNN-LSTM	6.66
Proposed	1.65

Table 6 and Figure 9 state that, compared comparatively in terms of RMSE, the results provided can give a satisfactory account of the proposed Adaptive Bilinear Transformer Network against different deep learning classifications. In that case, this is quite reasonable, and the model proposed by me

provides the highest accuracy in estimating the objective criterion; the RMSE value does not exceed 1.65. This value is much smaller compared with the other comparative methods, such as weight-adjusted bi-directional LSTM with the RMSE of 2.67, or the LSTMd model with the RMSE of 9.37. A large

reduction in RMSE shows that the proposed ABTNet is highly effective in minimizing the prediction error, thus proving its capability to make effective traffic condition forecasts. As such, the proposed architecture is far superior to any other architecture in the better representation of temporal dependencies and the complex patterns of traffic. Additional findings of the analysis are presented in Table 7 and Figure 10, which extend the double comparison of the proposed ABTNet with respect to MAE and RMSE performance against other Deep Learning Networks. The performance in the proposed model thus fits well with a value in both the metrics, as depicted below: MAE - 2.568 and RMSE - 2.146.

Namely, this value outperformed the others dramatically: MLP-MAE 4.307, MLP-RMSE 6.249, RF – MAE 4.594, RF – RMSE 6.888. The decline in both MAE and RMSE reveals that the proposed ABTNet not only provided more accurate traffic predictions, but it also had a lesser propensity to increase the level of error under different conditions. This enhances the resiliency and reliability characteristics of this model for live traffic forecasting, thus an advantage worth implementing in any smart transportation system. This indeed depicts the shift in transformation strength of ABTNet for traffic management as well as decision-making in vehicular networks.

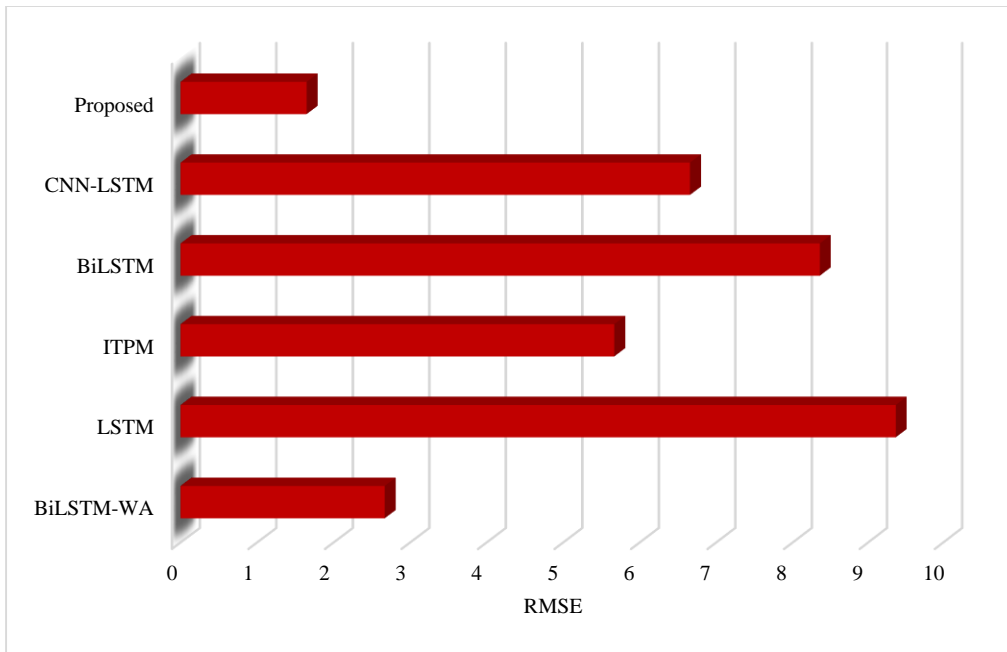


Fig. 9 Comparison with other state-of-the-art approaches based on RMSE

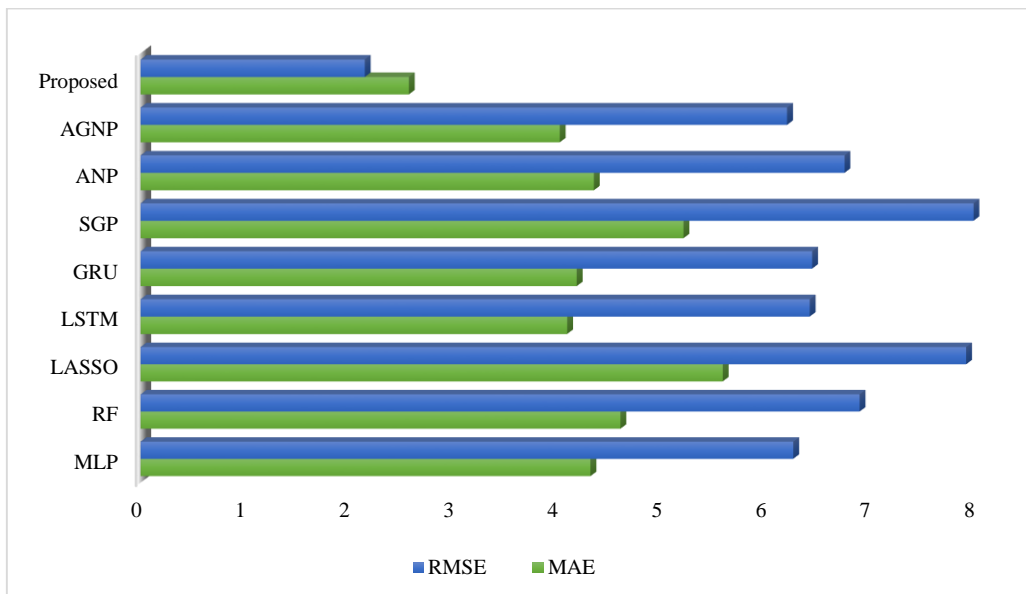


Fig. 10 Comparison with other state-of-the-art approaches based on RMSE and MAE

Table 7. Comparison with other deep learning architectures based on MAE and RMSE

Methods	MAE	RMSE
MLP	4.307	6.249
RF	4.594	6.888
LASSO	5.574	7.918
LSTM	4.084	6.407
GRU	4.176	6.430
SGP	5.198	7.989
ANP	4.340	6.742
AGNP	4.013	6.190
Proposed	2.568	2.146

4.1. Discussion

The benefit of the proposed ABTNet used in conjunction with the SiMoO optimizer is that intricate spatial and time-dependent relationships among traffic can be modeled simultaneously, which most of the existing models do not perform well. The bilinear transformer system allows getting one more contact with the traffic characters and allows the model to observe the minor alterations of the flow, density, and vehicle movement patterns. SiMoO also improves this learning by dynamically tuning the learning rate to converge faster with less error as compared to fixed parameter-based models. The informative training signals were more enriched by the diversity in the SUMO dataset and the richness in the preprocessing of spatiotemporal features as compared to the former research. Certainly, these innovations significantly reduce MAE and RMSE, improve Precision, Recall, and Accuracy, and deliver better generalization performance of the proposed traffic prediction model.

4.2. Constraints and Limitations in Real-Time Feasibility

Data used for traffic prediction in vehicular networks may contain several limitations and inherent biases that can affect model performance. First, traffic datasets are often collected from limited geographic regions or specific time periods, which may not fully represent diverse traffic behaviors across different cities or seasons. This can lead to sampling bias, where the model learns patterns that generalize poorly to unseen environments. Additionally, real-world traffic data frequently suffers from missing values, sensor malfunctions, and inconsistent reporting intervals, introducing noise that may skew predictions if not handled carefully.

Another concern is contextual bias, as sudden events like accidents, weather changes, or road closures might be underrepresented in the dataset, reducing the model's ability to adapt to rare but impactful scenarios. Moreover, data imbalance, such as having more samples from off-peak hours than high-congestion periods, can bias the model toward predicting smoother traffic conditions. Recognizing these limitations is essential, and future work should incorporate richer, multi-source data and domain adaptation strategies to minimize biases and enhance model robustness.

5. Conclusion

In this paper, a powerful traffic prediction system that comprises ABTNet and SiMoO is introduced. The proposed hybrid design incorporates the advanced deep learning algorithm with active optimization and can simulate the difficult spatiotemporal patterns in vehicular networks in a robust way. ABTNet framework is less restricted in traditional designs, as it proposes a more comprehensive architecture, implying time-dependent relationship of the given traits in a more detailed fashion, whereas SiMoO can adjust the learning rates to converge faster and achieve stability in training at a variety of traffic conditions. The framework, which was proposed, is exemplary in its execution against a number of measures.

As a matter of fact, it already has an impressive F1-score of 99, precision, and recall scores of over 98, and error rates of significantly lower order: incredible low RMSE of 1.65 and a MAE of 1.21, which confirms that ABTNet is more prone to attain higher accuracy and strength than the existing models of deep learning, including LSTMs, GRUs, Bi-LSTMs, and Transformer baselines. Nevertheless, despite these successes, the research admits that in real-world traffic data sets, there are several limitations, and they are: regional bias, non-observed values, sensor measurement noise, and bad representation of rare events such as accidents or sudden bottlenecks. Such issues may introduce bias in the prediction and reduce the model's generalizability. The efforts to resolve these problems will require a more diverse dataset, more comprehensive preprocessing pipelines, and more sophisticated mechanisms of mitigating contextual bias. Fundamentally, a proposed ABTNet-SiMoO system will be highly developmental in the field of smart traffic prediction, having high-accuracy, low-latency, and scalable prediction of real-time vehicular networks. The success of its bright results proves that it can streamline congestion and traffic control, help to adjust the traffic, and contribute to smarter, safer, and more efficient city movement systems.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

Competing Interests

The authors have no competing interests to declare that are relevant to the content of this article.

Ethical Approval

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author.

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