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AUTONOMOUS TRAFFIC PREDICTION: A DEEP LEARNING-BASED FRAMEWORK FOR SMART MOBILITY

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A B S T R A C T

The term deep learning-based framework for smart mobility refers to a concept or research article that suggests a framework for traffic pattern prediction using deep learning methods in the context of smart mobility. To improve traffic prediction skills and create more intelligent and effective transportation systems, the Autonomous traffic prediction: A deep learning-based framework for smart mobility idea proposes to make use of the potential of deep learning algorithms. In this study, a new Improved Spider Monkey Swarm Optimized Generative Adversarial Network (ISMSO-GAN) approach is introduced to forecast autonomous traffic for smart mobility. In this case, the GAN's classification effectiveness is increased by using the ISMSO method. The Regional Transportation Management Center's traffic dataset for Twin Cities' metro freeways is used to assess the success of the suggested approach. The noisy data from raw data samples are removed using the Adaptive Median Filter (AMF) filter. To extract the properties from the segmented data, a Kernel Principal Component Analysis (KPCA) is performed. The results of the research show that recommended methodology beats earlier approaches in terms of accuracy, Mean Square Error (MSE), Mean Absolute Error (MAE), and Prediction Rate. Our proposed method might considerably enhance traffic management and maximize resource allocation.

1. INTRODUCTION

The term "autonomous traffic prediction" refers to a system's or algorithm's capacity to foresee traffic conditions and base judgments on that information. Autonomous systems can forecast traffic congestion, travel times, and the best routes by assessing a variety of data sources, including historical traffic patterns, real-time sensor data, meteorological conditions, and even social events. Various methods and strategies are used for autonomous traffic prediction, including The technology that may find repeating traffic congestion patterns at certain hours, days, or places by examining past traffic patterns. Future traffic problems may be predicted with the use of the knowledge. Constant analysis of the data is conducted to forecast upcoming and present traffic conditions (Shakarami et al., 2021). Traffic patterns are significantly influenced by the

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weather. Autonomous systems may anticipate how weather conditions, such as rain, snow, or fog, would impact traffic flow by including meteorological data in the prediction models, and they can then modify their plans appropriately. Traffic may be greatly impacted by large-scale events, festivals, holidays, and road closures because of construction or parades. To forecast changes in traffic patterns and suggest other routes, autonomous systems may consider information about such occurrences. Large amounts of traffic data may be analyzed and processed by sophisticated machine learning algorithms, continually enhancing their forecasting skills. More precise traffic forecasts may be made because of these algorithms' ability to recognize intricate patterns and relationships. Autonomous traffic prediction aims to provide ability to make smart choices, such as route planning and speed adjustments, to improve traffic flow and ease congestion. Autonomous systems may contribute to more effective transportation, increased road safety, and better overall travel experiences by predicting traffic circumstances (Mauri et al., 2021).

Utilizing the strength of deep learning algorithms to examine multiple data sources and make wise judgments to optimize travel and enhance mobility is the basis of a deep learning-based framework for smart mobility. Here is a list of the elements that may make up such a framework: Data from many sources, such as traffic sensors, GPS data from moving cars, meteorological data, social media feeds, and other pertinent data streams, must first be gathered. The information offers a thorough picture of the present traffic situations and the variables that affect mobility. To eliminate noise, manage missing values, and standardize the format for analysis, the acquired data has to be preprocessed. To extract useful information from raw data, preprocessing may comprise processes like data cleansing, normalization, and feature engineering. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformers are a few examples of deep learning models that may be used to discover intricate patterns and correlations in data (Wang et al., 2019).

The models can handle a variety of data kinds, including time series, text, and picture data, and derive insightful information. Deep learning models may be taught to forecast travel times, traffic patterns, and degrees of congestion. The models may produce precise forecasts of traffic conditions in the future by examining historical traffic data, real-time sensor data, and other pertinent parameters (Razali et al., 2021). The knowledge may aid in route optimization, traffic flow management, and congestion relief. Route optimization algorithms may include deep learning models to recommend the most effective routes depending on anticipated traffic circumstances. The algorithms can dynamically modify routes to avoid congestion and save travel time by taking into account both historical trends and real-time traffic data. Real-time decision-making using deep learning models is another option. For instance, autonomous cars may use deep reinforcement learning algorithms to learn the best practices depending on the surroundings and the current traffic situation (Nama et al., 2021). With the aid of the models, automobiles may safely and efficiently maneuver through challenging traffic situations. The framework may include methods for ongoing learning, enabling deep learning models to change and advance over time. The system can adapt to shifting traffic patterns and changing mobility needs by continually gathering fresh data and retraining the models. A smart mobility framework may allow intelligent decision-making for many stakeholders, including autonomous cars, traffic management systems, and transportation planners, by using the power of deep learning to deliver real-time traffic forecasts, optimize routes, and supply services. A framework like this may support increased productivity, less traffic, more safety, and generally better mobility solutions (Nacef et al., 2022).

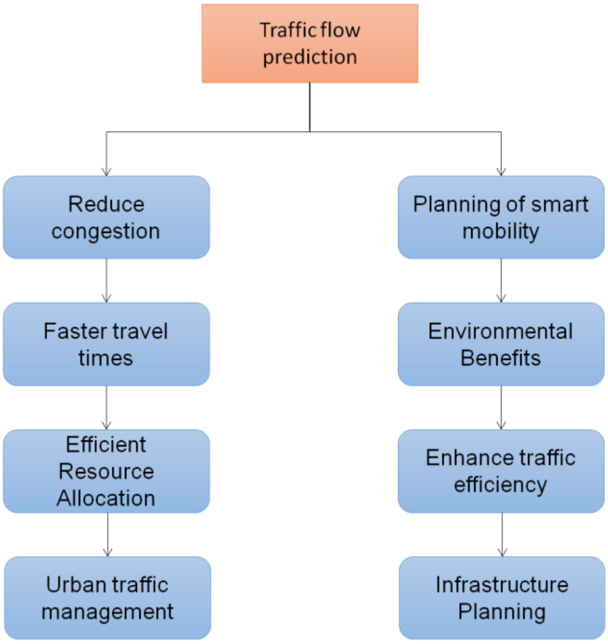

Figure 1. Benefits of Traffic flow prediction

Predicting traffic flow has several advantages which are shown in (Figure 1) for promoting mobility in general and for strengthening transportation systems. Here are a few significant benefits: The most effective routes may be selected in real-time and navigation systems thanks to accurate traffic flow estimates. Travel times may be cut greatly by choosing the best routes and avoiding crowded regions, which results in less time sitting in traffic and more efficiency overall. Transportation authorities and traffic management systems use traffic flow prediction to proactively find and handle congested areas. By identifying places that are expected to experience congestion, actions may be done in advance to reduce it. The traffic signal timings can be changed, dynamic lane management can be put into place, and other routes can be suggested to disperse traffic more equally (Kim et al., 2022). By enabling autonomous to foresee probable traffic snarls and dangerous circumstances, traffic flow prediction helps to increase traffic safety. With this knowledge, the proper measures and modifying their style as necessary, lowering the risk of accidents and improving general road safety. The use of traffic flow prediction improves scheduling and planning for public transportation networks. To make sure that buses, trains, and other forms of public transportation are in line with the anticipated traffic patterns, public transit organizations may optimize routes and schedules by forecasting traffic conditions (Zhang et al., 2022).

Traffic flow prediction lowers emissions and fuel use by streamlining traffic and easing congestion. A greener and more sustainable transportation system may be created via route design that is effective and cuts down on idle time. The actions can also result in fewer carbon dioxide emissions and better air quality. Emergency response services can more easily and rapidly navigate through traffic with the help of traffic flow prediction (Tang et al., 2021). An emergency may be sent along the quickest and easiest routes by precisely forecasting traffic conditions, allowing quick help in urgent circumstances. Prediction of traffic flows produces useful data that may be used in transportation planning. Urban planners and legislators may make educated judgments about infrastructure development, road extension, traffic signal optimization, and improvements to public transit by using historical traffic flow data and projections. Traffic flow prediction improves travel times, eases congestion, boosts safety, reduces environmental impact, and informs data- transportation planning, which benefits people, communities, and transportation authorities. Transportation systems may become more effective, sustainable, and responsive to commuters' and tourists' requirements by using precise traffic flow projections (Lilhore et al., 2022). For autonomous traffic prediction in smart mobility, the Improved Spider Monkey Swarm Optimized Generative Adversal Network (ISMSO-GAN) architecture provides a potent mix of deep learning, optimization, and generative modeling approaches. As a result, more accurate, effective, and adaptable traffic projections are made, which eventually results in more intelligent and efficient transportation systems.

Key Contributions:

The autonomous traffic prediction framework based on ISMSO-GAN may make a substantial contribution to smart transportation. These significant contributions are listed:

- To allow precise traffic forecasting, in-the-moment observation, adaptive traffic management, and autonomous traffic prediction utilized to improve user experiences and safety.
- Traffic integration enables transportation systems to run more effectively, lessen congestion, and improve overall mobility for people and communities by using cutting-edge machine learning methods like ISMSO-GAN.

The remainder of the document is structured as follows: Concerning the aims or objectives of the research, segment 2 describes the preceding study and identifies any deficiencies or discrepancies. In segment 3, the research methodology and techniques used to collect and evaluate the data are described along with recommendations for future research based on the findings. Before presenting the research results concisely and systematically, analyzing and explaining them in light of the study aims or objectives, we go through the Discussion and results in Segment 4 first. Segment 5 provides an overview of the study's main elements, as well as its relevance and contributions, potential ramifications for practice or policy, and potential future study areas.

2. RELATED WORKS

(Miglani and Kumar 2019) investigated into autonomous cars to plan their route and make adaptive choices about their surroundings, traffic flow prediction is crucial. However, because of the non-linear complicated interaction between the spatial and temporal data acquired from the environment during the aforementioned adaptive choices made by the traffic prediction, current machine learning methods may not be immediately relevant in the setting. (Shao and Sun 2020) suggested a technique for a connected and autonomous car to cross the junction that reduces fuel consumption. It is created as a control system that combines speed optimization and connectivity-enabled traffic prediction. The traffic forecast is based on a traffic flow model and is adaptable to mixed traffic situations including both connected and unconnected cars on the route. 'Partial' assessment of the traffic situations is provided by real-time data from linked cars and signal lights. (Lee et al., 2020) developed a machine learning-based traffic management system and a routing technique that dynamically chooses AVS routes with lower congestion rates. The study forecast congestion for key bottleneck sites and used the forecasts to direct all cars' routes adaptively to prevent congestion. To assess the predicted effectiveness of four well-known algorithms, the study performed an experimental study. To show the value and superiority of the suggested strategy, research carried out a simulation study using information from semiconductor manufacturers. (Shah et al., 2021) analyzed the Long short-term memory (LSTM), gated recurrent unit (GRU), and hybrid CNN-LSTM models used to solve the challenge Study demonstrated that our deep learning models beat the conventional linear regression technique by training our models over 6 months using real traffic flow data supplied by the

California Department of Transportation (Caltrans). For the traffic flow prediction challenge, architectural analysis of deep learning models is also conducted. (Mall et al., 2023) preferred the number of vehicles on the road has increased dramatically in smart cities over time, leading to serious concerns including traffic, accidents, and a wide range of other problems. The advanced traffic control system now in use is built on image processing.

(Prarthana et al., 2022) familiarized to provide a comparison of different vehicle detection and classification techniques and to provide the reader with the current AI-based classification algorithms. Based on the kind of input, such as an image or video, the current classification algorithms may be divided into two groups. The Intelligent Transportation System (ITS), which combines technologies including artificial intelligence, image processing, data mining, and sensors, can watch the road, start autonomous identification, and effectively manage traffic on the road by using the technologies.

(Yu et al., 2020) examined the features, a forecast of the vehicular Edge processing capability, and a look at the Wireless Access in Vehicular Environment (WAVE) architecture are all included in a simulation of Harbin city. Utilizing the architecture that has been presented, the Study also evaluated a traffic efficiency application to cut down on waiting times and fuel use. The outcomes of the simulation demonstrated the capability of the suggested framework to provide dynamic coupling between the ITS Edge computing solutions for future city models. (Jaffry and Hasan 2020) explored models for autonomous cellular traffic prediction using deep learning methods like recurrent neural networks and long short-term memory. (Alghmgham et al., 2019) evaluated the creation of an autonomous traffic and road sign detection and identification system using the Deep Convolutional Neural Network. The suggested system detects and recognizes images of traffic signs in real-time. The additional article also includes a freshly created database of 24 distinct traffic signs that were gathered from Saudi Arabian roadside locations. The photographs were captured under various circumstances and from various perspectives. (Li et al., 2022) suggested a vehicle trajectory prediction using the Clustering Convolution-Long Short-Term Memory (CC-LSTM) model. Similar trajectories of nearby cars are grouped using the fuzzy clustering approach to extract their temporal properties. By using density clustering, the characteristics of the historical trajectory are classified, and similarities between segments that are employed as the spatial features of the trajectory of the target vehicle are found. The Las Vegas Wrapper (LVW) approach fuses the filtered spatio-temporal characteristics to provide fresh input data for the Convolution-LSTM network to generate predictions.

3. EXPERIMENTAL PROCEDURE

In this section, the approach used to build the model was defined, the main stages that were taken to build the model were described, and a detailed explanation of how the steps of the recommended model in (Figure 2) were created was given. There are four parts to this discussion: Information collecting is the focus of the first phase. In the second part, we'll talk about the process, feature selection and extraction methods, and other data pre-processing methods. The third part, which describes the effort done to create the recommended model and gather the fundamental experiences, is where the most important information is offered. In the fourth stage, the performance of each existing and new model is evaluated by contrasting the corresponding parameters.

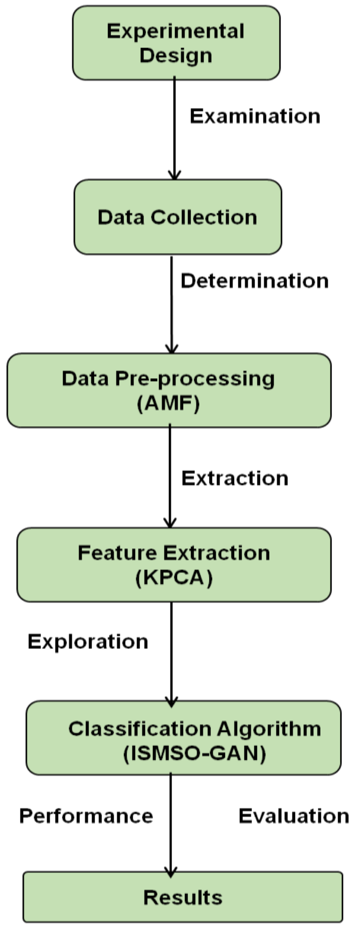

Figure 2. Experimental design of Autonomous traffic prediction for smart mobility

3.1 Dataset

The training set is made up of the data from January 12, 2018, to June 11, 2018, while the test set is made up of the data from June 17, 2018, to January 12, 2019. In our research, the main goal of data mining is to examine the data rules from 6:00 to 21:00, which is the busiest time of day (Hou et al., 2021).

Traffic Data

The Regional Transportation Management Center (https://www.d.umn.edu/tdrl/traffic/) is the source of traffic data for the metro freeways in the Twin Cities. The raw data are gathered from more than 4,500 loop detectors at intervals of 30 seconds. The No. 644 detector data with the fewest mistakes and omissions between January 12, 2018, and January 12, 2019, were chosen. The data are organized into a table with 5-minute intervals during the preprocessing step. In the meantime, the errors and omissions are fixed using the time similarity concept. The processed traffic data is shown in (Table 1).

Table 1. Traffic Flow dataset (Hou et al., 2021).

Time	Flow
2018/1/12 6:00	67
2018/1/12 6:05	86
…….	…….
2018/1/12 8:05	163
2018/1/12 8:10	167
…….	…….
2018/1/12 21:00	47

By using the historical average (HA) approach, we create a time-flow correlation expression to show the periodicity of traffic data under weather disturbance. Working days and nonworking days are separated from the training set, and the average flow within each time slice is counted and used as a representation of the time slice. The following is an example of the time-flow correlation expression on a time slice in Formula (1):

$$x_t^{timecode} = \frac{1}{n}\sum_{j=0}^{n} x_{i,j}^{flow} \tag{1}$$

Where $x_{i,j}^{flow}$ shows the progression of time slice i on day j.

3.2 Data Pre-Processing using Adaptive Median Filter (AMF)

The AMF method is an improved version of the conventional median filter. Through spatial processing, impulse noise is reduced. The AMF classifies each pixel in the skin image together with its neighboring pixels to determine if noise is present or not. It operates better than other filters since it guards the fine visual details and reduces non-impulse noise. Additionally, there is a good chance that it can adjust to abrupt loudness. The mean channel and the median channel both have an identical impact on the disorder of a picture. The median channel for two descriptions could vary, as in Formula (2).

$$\mathrm{med}(\mathrm{n_k}) = \begin{cases} \mathrm{n_i} + 1^{\mathrm{a}} = 2\mathrm{i} + 1(\mathrm{ODD})) \\ \frac{[\mathrm{n_i}+\mathrm{n_{i+1}}]}{2}\mathrm{a} = 2\mathrm{i}(\mathrm{even}) \end{cases} \tag{2}$$

Here n_i is the i^{th} the biggest observed data and n_1; n_2; n_3... n_i are the observed data. Consider a situation where there are seven samples overall in the data collection 2, 3.5, 1, 3, 1.5, 4 and and the median filter yields an output of 2.5. If the pulse is n + 1 or longer, the signal will be kept; otherwise, it will be eliminated from the series. Because it may minimize pulse noise while keeping local characteristics, the median filter differs from other filters. This method then sends the signal it produces to the feature extraction stage.

3.3 Feature Extraction by using Kernel Principal Component Analysis (KPCA)

An approximate covariance matrix of the data in Formula (3) is diagonalized using a basis transformation known as Principal Component Analysis (PCA).

$$\mathrm{D} = \frac{1}{\mathrm{k}}\sum_{\mathrm{i=1}}^{\mathrm{k}} \mathrm{v_l}\mathrm{v_i^S} \tag{3}$$

The orthogonal projections onto the Eigenvectors or the new coordinates in the tile Eigenvector basis are principal components. In this work, this setting is further developed into a nonlinear setting of the following kind. If the data were initially nonlinearly mapped onto a feature space using Formula (4),

$$\Phi: Q^M \rightarrow E, v \rightarrow V \tag{4}$$

We'll show that, for certain values, even if it has arbitrarily large dimensionality, we can still do KPCA in E.

For now, let's assume that Formula (5) translates data into feature space. KPCA for the covariance matrix,

$$\overline{\mathrm{D}} = \frac{1}{\mathrm{k}}\sum_{\mathrm{i=1}}^{\mathrm{k}} \Phi(\mathrm{v_l})\Phi(\mathrm{v_l})^{\mathrm{S}} \tag{5}$$

KPCA, a nonlinear version, is often used in denoising and wavelet transform applications. When the manifold is linearly buried in the observation space, the standard PCA method attempts to minimize the number of dimensions. To fulfill the needs of the PCA, the second component of KPCA, the manifold is linearized using the kernel approach, one of the two components. KPCA uses feature mapping to automatically transform data into a pairwise formula between the mapped data in the feature set. This pairwise formula is computed by the kernel. Finding a suitable kernel that linearizes the surface in the feature space while taking the geometry of the input space into account is challenging. For a poor projection that does not meet these requirements, KPCA's nonlinear dimensionality reduction would be useless.

3.4 Improved Spider Monkey Swarm Optimized Generative Adversarial Network (ISMSO-GAN)

Improved Spider Monkey Swarm Optimized Generative Adversarial Network" (ISMSO-GAN) seems to be a synthesis of many ideas and methods. To better comprehend each part, let's dissect the situation: The spider monkeys' foraging behavior served as the model for the nature-inspired optimization algorithm SMSO. To address optimization issues, it imitates the group dynamics and foraging strategies of swarms of spider monkeys. Spider monkeys are renowned for being nimble and adaptable, and SMSO makes effective use of these traits to effectively search the domain. A generator network and a discriminator network are trained concurrently as part of the generative modeling approach known as GAN. While the discriminator network works to separate genuine samples from false ones, the generator network creates artificial data samples. In many different sectors, GANs have shown their ability to produce realistic and varied samples. It is intended to use SMSO's optimization skills while including GAN's generative modeling capabilities when SMSO and GAN are combined. The overall concept is to use the GAN's generator network to produce possible solutions for the optimization issue and the discriminator network to assess the quality of these solutions. The particular implementation may vary. The SMSO algorithm then employs the input from the discriminator to direct the search and incrementally raise the quality of created solutions. According to the phrase used, "ISMSO-GAN" denotes a Spider Monkey Swarm Optimization method that has been modified in some way and merged with a Generative Adversarial Network.

a) Spider Monkey Swarm Optimization

Here are more details about the main parts of Spider Monkey Optimization:

- **Setting up the Population**

Each spider monkey's starting location in the population is represented by its initial parameters, TN_{or} (o=1, 2... N), an N-D vector where N specifies the number of issue variables to be improved. Each SM pinpoints an achievable goal that might fix the issue. It is defined as Formula (6), for each $TN_{or}(1)$

$$TN_{or} = TN_{minq} + VQ(0,1) \times \left(TN_{maxq} - TN_{minq}\right) \quad (6)$$

Where TN_{maxq} and TN_{minq} are minimum and maximum values of TN_{or} in the direction and (0, 1).

- **Local Leader Phase**

At this step, the SMO updates its actual role related to the decisions of its local group and local leader (LL), and it also determines the fitness values for the positions of any newly arrived monkeys. This is the stage when Spider monkeys must increase their fitness by replacing their previous positions with new ones. Formula (7) for the othTN's position is as follows :

$$TN_{newor} = TN_{or} + VQ(0,1) \times (KK_{kr} - TN_{or}) + VQ(-1,1) \times (TN_{qr} - TN_{or}) \quad (7)$$

In this case, the oth dimensions of the kth LL position correspond to the rth component of the kth SM. The dimensional TN_{qr} is the rthTN picked at random from the kth group where r is less than or equal to V in the rth dimensions.

- **Global Leader Phase**

Members of both the GL and LL groups share their insights to aid in the spider monkeys' stance adjustment. The Formula (8) coordinates may be found by,

$$TN_{newor} = TN_{or} + VQ(0,1) \times (HK_{kr} - TN_{or}) + VQ(-1,1) \times (TN_{qr} - TN_{or}) \quad (8)$$

Where (r = 1, 2,) N is a randomly chosen index and GLj is the rth dimension of the GL location. At the GLP stage, spider monkeys (TN_{or}) have their positions updated according to the ri values of the probabilities that are taken into account for calculating their fitness. This manner, the most qualified applicant may best present themselves. The following Formula (9) may be used to determine the probability of ri:

$$ri = (fitness\ ix / fitness\ max)\ +\ 0.1 \quad (9)$$

Where fitness max is the highest possible fitness level for the oth N's group. In addition, the optimal location is selected by calculating a new fitness algorithm that relies on the created position and comparing it to the previous fitness parameter.

- **Global Leader Learning Segment**

In the GLL segment, the pessimistic model is used to update and perform the feature extraction. The population is used to choose and create the fitness function value. The optimal value of the place determines the value of the world leader. Instead of updating, the value is increased by one and stored in the Global Limit Count variable.

- **Local Leader Learning Phase**

According to the fitness values of a community organization, the LLL is changed in the SM location, making it the best possible choice for the local community. It's worth whatever the current regional authority decides it's worth. As it increases by one with each new LLC, no additional updates are supplied.

- **Local Leader Decision Phase**

If the LLD doesn't update its location using initial randomization or the knowledge of the GL and LL, it does so using the perturbations rate which is represented in Formula (10),

$$TN_{newor} = TN_{or} + VQ(0,1) \times (HK_{kr} - TN_{or}) + VQ(0,1) \times \left(TN_{qr} - KK_{or}\right) \quad (10)$$

- **Global Leader Decision Phase**

At this point, the GL placement has been kept an eye on for a while. After that, the GL creates subgroups of the population, always starting with two and increasing the number as much as is practical. New groups are formed and LLL procedures to choose the LL are started at the GLD stage. The GL can't move from where it is. Additionally, it emulates the spider monkey's fusion-splitting social structure by merging all of the smaller groups into a single, supergroup when the ideal number of separate groups is attained.

By adding up the proportional importance of each trait, fitness is determined. Based on the objective variables, a score is assigned to each component of the input data. The importance of the feature is determined based on the impurity of the junction with the values that are reflected in Formula (11) when the probability of reaching the node decreases before it is reached. By dividing the ratio of the observed numbers by the total number of specimens, we may get the likelihood of the node. We use it to calculate the fitness function to choose features in the best way possible.

$$fitness_{feature\ importance} = \frac{Number\ of\ specimens\ that\ reach\ the\ nodes}{Total\ number\ of\ samples} \quad (11)$$

Utilizing the low-level co-evolutionary traits, the SMSO hybridized algorithm creates the hybrid mixed capability. There are merge and combine options available as part of the basic hybrid capability which shows in Formula (12) and (13). Co-evolutionary is used because variations are employed sequentially, in parallel. The two types are combined, and both contribute to the creation of answers to the challenges. With this adjustment, the hierarchical SMSO generates variations using the strength of SMSO. The velocity is revised using the combined SMSO variations, as suggested,

$$u_j^{l+1} = x * (u_j^l + d_1 q_1\left(w_{1-} w_j^l\right) + d_2 q_2 (w_{2-} w_j^l) + d_3 q_3 (w_{3-} w_j^{l+1})) \quad (12)$$

$$w_j^{l+1} = w_j^l + u_j^{l+1} \quad (13)$$

Hence, a function is used to choose the optimal set of characteristics from the subgroup, and data augmentation is calculated if there is any ambiguity among the features.

b) Generative Adversarial Network (GAN)

The use of Generative Adversarial Networks (GANs), a novel method of producing synthetic traffic data, may be useful for traffic prediction applications. A generator and a discriminator are the two primary parts of GANs. The generator in the context of traffic prediction is in charge of producing artificial traffic data, while the discriminator assesses the veracity of the created data by separating it from actual traffic data. A deep learning model known as a GAN consists of two neural networks: a generator and a discriminator. The goal of GANs is to produce new data that closely matches a given training dataset. The generator network creates synthetic data samples from the input of random noise. The discriminator network is then fed these samples as well as actual data samples from the training dataset. The discriminator's objective is to accurately distinguish between genuine and fake data, while the generator's objective is to generate data that the discriminator is unable to distinguish from real data. The generator and discriminator are regularly practiced throughout training in a two-player minimax game. The generator tries to fool the discriminator to improve its ability to generate realistic data, while the discriminator strives to enhance its ability to distinguish between genuine and fake data. Through this adversarial training process, both networks are improved over time. When the generator is taught, it may produce fresh data samples that mirror the initial training data. GANs have been employed with success in several applications, including the creation of images, texts, and even videos. They have completely changed the generative modeling industry and significantly improved the synthesis of realistic data. To get effective results, GANs must be carefully trained and tuned since they are complicated models. Additionally, there are difficulties in assessing the quality of produced samples, and GAN training might sometimes be unstable. However, with improvements in GAN designs and training methods, this field of study is still active and has made significant strides in producing high-quality synthetic data. A research framework that uses GANs in the context of traffic prediction and smart mobility is referred to as a deep learning-based framework for smart mobility. This framework makes use of deep learning methods to forecast traffic patterns and provide autonomous systems with the information they need to make wise judgments. This framework's primary goal is to use GANs to produce synthetic traffic data that closely reflect actual traffic circumstances. The discriminator network learns to distinguish between actual and produced traffic data while the generator network learns to create realistic traffic situations by training on historical traffic data.

4. RESULTS AND DISCUSSION

4.1 Results

Frameworks based on deep learning have shown promising results in several traffic prediction applications, including traffic flow prediction. Deep learning algorithms may understand complicated patterns and correlations to generate precise forecasts about traffic conditions by using vast volumes of historical and real-time traffic data.

a) Accuracy

The ISMSO-GAN framework may effectively capture the underlying patterns and dynamics of traffic behavior, leading to valid predictions, which are represented in Formula (14). A high accuracy in traffic prediction suggests that this is the case. The complexity and dynamic nature of traffic networks make it difficult to achieve high accuracy in traffic forecast, and there may be underlying uncertainties and unpredictability that impact the prediction accuracy.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{14}$$

Table 2. Numerical outcomes of the accuracy for existing and proposed methods.

Methods	Accuracy (%)
RNN (Jaffry and Hasan 2020)	42
DCNN (Alghmgham et al., 2019)	58
CC-LSTM (Li et al., 2022)	76
ISMSO-GAN [Proposed]	92

(Figure 3) shows how accurate the suggested and existing approaches are compared. Accuracy levels are often reported as a percentage of the total. Both the existing method and the suggested method run the risk of producing inaccurate estimates. The accuracy rate of the suggested approach, ISMSO-GAN, is 92%, compared to accuracy rates of 42%, 58%, and 76% for RNN, DCNN, and CC-LSTM. The proposed approach thus has the greatest accuracy rate. The accuracy of the recommended approach is shown in (Table 2).

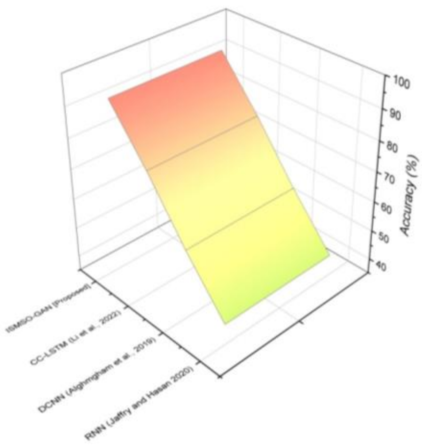

Figure 3. Comparison of accuracy for existing and proposed methods

b) Mean Absolute Error (MAE)

The average absolute difference between expected and actual values is measured using the MAE metric in the context of traffic prediction. When forecasting traffic variables like traffic flow, congestion levels, or trip times autonomously, MAE measures the average magnitude of mistakes. To calculate MAE for traffic prediction, the anticipated values such as expected traffic flow and the corresponding actual values (ground truth) are compared. Calculated, added together, and divided by the total number of samples are the absolute disparities between each projected value and its matching actual value. According to Formula (15),

$$MAE = \frac{1}{m}\sum_{j=1}^{m}\left|\hat{\phi}_j - \phi_j\right| \tag{15}$$

Table 3. Numerical outcomes of Mean Absolute Error for existing and proposed methods.

Methods	Mean Absolute Error (%)
RNN (Jaffry and Hasan 2020)	28
DCNN (Alghmgham et al., 2019)	32
CC-LSTM (Li et al., 2022)	46
ISMSO-GAN [Proposed]	58

The MAE of the proposed and existing techniques is shown in (Figure 4). MAE severity is often described as a percentage of the total. Both the existing method and the suggested one might lead to inaccurate estimates. In comparison to RNN, DCNN, and CC-LSTM, which have error rates of 28%, 32%, and 46%, respectively, the suggested approach, ISMSO-GAN, has a low Mean Absolute error rate of 58%. The recommended approach thus has a low Mean Absolute rate. The proposed strategy's error rate is shown in (Table 3).

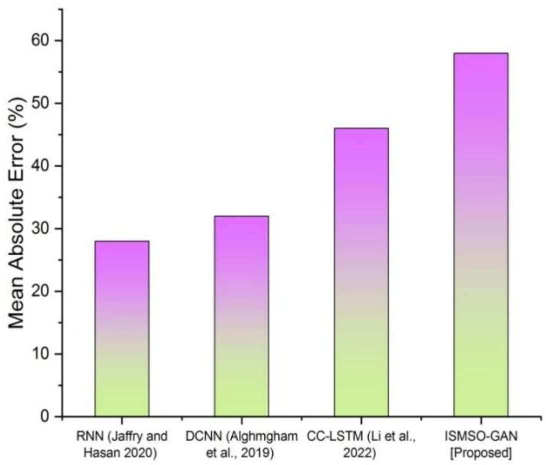

Figure 4. Comparison of Mean Absolute Error for existing and proposed methods

n − Total number of samples

$\hat{\phi}_j$ − Prediction Values

ϕ_j − Actual Values

c) Mean Square Error (MSE)

MSE is yet another widely used statistic for assessing the efficacy of prediction models, including those used in autonomous traffic prediction. Between the expected and actual values, it calculates the average squared difference. The squared difference between each predicted value and its matching actual value is taken into account when calculating the MSE which are represented in Formula (16). This squared difference is then added together, and divided by the total number of samples,

$$MSE = \frac{1}{m}\sum_{j=1}^{m}\left(\hat{\phi}_j - \phi_j\right)^2 \quad (16)$$

Table 4. Numerical outcomes of Mean Square Error for existing and proposed methods.

Methods	Mean Square Error (%)
RNN (Jaffry and Hasan 2020)	31
DCNN (Alghmgham et al., 2019)	37
CC-LSTM (Li et al., 2022)	52
ISMSO-GAN [Proposed]	65

The MSE of the proposed and existing techniques is shown in (Figure 5). MSE severity is often described as a percentage of the total. Both the existing method and the suggested one might lead to inaccurate estimates. In comparison to RNN, DCNN, and CC-LSTM, which have error rates of 31%, 37%, and 52%, respectively, the suggested approach, ISMSO-GAN, has a low Mean square error rate of 65%. The recommended approach thus has a low Mean square rate. (Table 4) displays the proposed strategy's error rate.

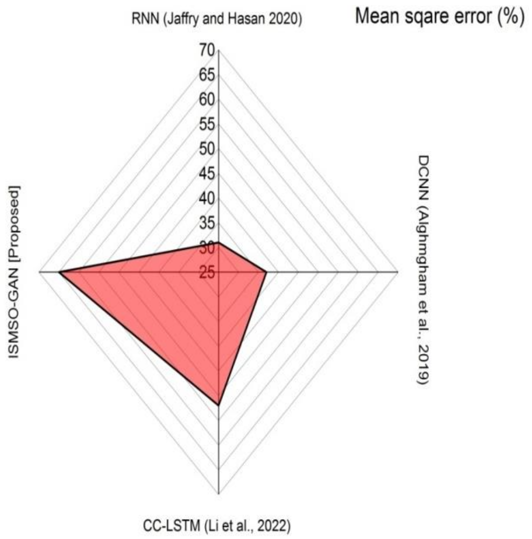

Figure 5. Comparison of Mean Square Error for existing and proposed methods

d) Prediction Rate

The accuracy of the autonomous traffic prediction framework may be evaluated using several performance metrics, including prediction rate. A greater prediction rate suggests more accurate and reliable traffic pattern predictions, which may help streamline traffic management tactics, boost safety precautions, and upgrade overall smart mobility systems, as shown in formula (17).

$$\text{Prediction Rate} = (\text{Number of Correct Predictions} / \text{Total Number of Predictions}) \times 100 \quad (17)$$

Table 5. Numerical outcomes of prediction rate for existing and proposed methods.

Methods	Prediction rate (%)
RNN (Jaffry and Hasan 2020)	40
DCNN (Alghmgham et al., 2019)	56
CC-LSTM (Li et al., 2022)	74
ISMSO-GAN [Proposed]	85

The prediction rate of the proposed and existing techniques is shown in (Figure 6). A percentage of the total is often used to represent the degree of prediction rate. Both the existing method and the suggested one might lead to inaccurate estimates. ISMSO-GAN, the suggested approach, predicts with an prediction rate of 85%, compared to rates of 40%, 56%, and 74% for RNN, DCNN, and CC-LSTM. As a result, the recommended approach has the best rate of prediction. (Table 5) displays the proposed strategy's prediction rate.

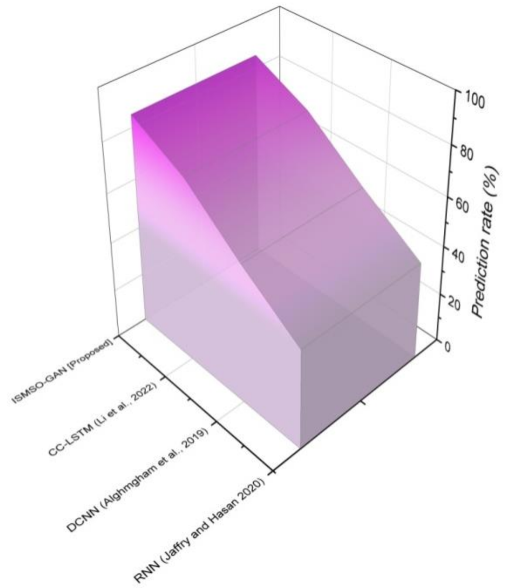

Figure 6. Comparison of prediction rate for existing and proposed methods

4.2 DISCUSSION

Intelligent mobility solutions must include autonomous traffic prediction since it allows effective traffic management and enhanced transportation services. ISMSO-GAN, a deep learning-based system, presents a viable strategy to handle the difficulties in traffic prediction. ISMSO-GAN may learn from real-world traffic data and provide predictions that closely reflect the actual traffic patterns by training these networks together. The capacity of ISMSO-GAN to recognize intricate and nonlinear correlations in traffic data is one of its main features. Traditional traffic prediction models sometimes make simple assumptions and overlook the complex interconnections between the many variables affecting traffic flow. ISMSO-GAN can capture these intricate correlations and provide more precise predictions by using deep learning methods.

5 CONCLUSION

A deep learning framework for smart mobility based on ISMSO-GAN proposes a unique method for forecasting traffic patterns in autonomous traffic systems. The research shows how deep learning methods may be used to estimate traffic conditions and events in the future with accuracy. The suggested framework enhances the precision and dependability of traffic forecasts by using ISMSO-GAN's capabilities, allowing for more efficient traffic management and smart mobility system optimization. Metrics like accuracy and prediction rate are used to gauge the framework's effectiveness. Results show that the deep learning-based strategy produces positive outcomes, with high rates of prediction and accuracy. This shows that the approach might enable preemptive traffic management decision-making and provide insightful information about possible traffic patterns. The study also emphasizes how crucial precise traffic prediction is for autonomous systems since it makes it possible to allocate resources effectively, control traffic, and take better safety precautions. The suggested architecture advances smart transportation systems by offering accurate and dependable traffic forecasts. It's crucial to recognize some of the framework's limits, however. The effectiveness of the deep learning model may be impacted by variables including data accessibility, model complexity, and computing resources. To address these issues and look at approaches to improve the scalability and generalizability of the system, further study is necessary. In conclusion, we preferred a paradigm based on deep learning that shows promise for autonomous traffic prediction in smart transportation systems. The findings imply that the suggested strategy has the potential to considerably enhance traffic management and optimize resource allocation, opening the door for future autonomous transportation systems that are more effective and dependable.

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