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OPTIMIZING LSTM HYPERPARAMETERS WITH WHALE OPTIMIZATION ALGORITHM FOR EFFICIENT FREIGHT DISTRIBUTION IN SMART CITIES

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Abstract. Smart cities save logistics and operational expenses by optimizing freight distribution. This paper presents LSTM hyperparameter adjustment to optimise freight allocation using the Whale Optimization Algorithm (WOA). Traditional hyperparameter tuning struggles with freight logistics' complexity and dynamism. WOA, a revolutionary bio-inspired optimization approach, finds optimal LSTM network hyperparameters. Our integrated solution fine-tunes LSTM hyperparameters using WOA to increase forecast accuracy and efficiency. The solution is tested on many smart city freight distribution scenarios. To prove the method works, prediction accuracy, computing efficiency, and convergence rate are measured. To determine how well the model detects data patterns and variations, the authors compare anticipated and real traffic flows using MAE, MSE, RMSE, etc. The proposed model's root mean squared error is 0.23912122600654664 and achieved MAE value of 0.17255859883764077.The WOA-optimized LSTM model outperforms hyperparameter tuning in prediction accuracy and convergence speed. This optimises resource allocation and reduces environmental effect in freight distribution, enabling smart city concepts. These findings affect urban logistics and encourage more investigation.

Key words: LSTM model, Whale optimization model, Machine learning, Freight distribution, Smart Cities.

1. Introduction. Urban freight distribution is making the goods and services needed to support businesses, communities, etc., move across cities as smoothly as possible. It is a crucial element when it comes to modern economies. Urban areas pose a variety of barriers to traditional logistics systems, such as traffic congestion or environmental concerns. In light of these challenges, there has been a growing number of research works focusing on the use of advanced technologies for optimizing urban freight distribution processes with an increasing tendency towards utilizing machine learning (ML) approaches. In this paper, the development of a Hybrid Machine Learning-Based Platform (HMLBP) with an emphasis on improving freight distribution performance in urban areas is introduced. The HMLBP seeks to change how logistics operations in dynamic urban landscapes are managed and carried out by using the best of machine learning algorithms, along with traditional optimization techniques. The convergence of machine learning with freight distribution provides a lot more added value. Machine learning algorithms are able to process a large volume of historical data trying to identify patterns, trends or dependencies doing so with much less certainty than anything the above-mentioned methods could offer. In addition, machine learning can also map predictive models by predicting demand and traffic as well delivery requirements which could help logistics operators to take real time decisions in action (Abadi et al., 2016; Adikari & Amalan, 2019).

As a critical part of how cities work, urban freight distribution gets goods from businesses to consumers. While global trade has opened up a wider array of products and services, there is no doubt that the complexity stakes in urban freight logistics have increased amidst rising e-commerce, population density. As a result, the economic competitiveness against environmental sustainability and urban liveability has become an increasing theme for city planners, policymakers or logistics companies. Over the years, various constraints — traffic

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congestion, insufficient infrastructure and emissions/vehicle use regulations — direct supply chains that provide service to city regions. Freight distribution that is efficient ensures timeliness in the delivery of goods with a reduced toll on both environmental and public health.

Distribution has traditionally been based on road transport, which is still the largest form of freight for delivery. The increase in the number of delivery vehicles, however — contributing to even more urban congestion (and hence higher levels of air pollution and noise) The research team was well aware that the World Health Organization calculates millions of deaths every year on account of air pollution, and a good part comes from transport emissions. The growth in cities, meanwhile, drives freight demand higher and the pressure on existing infrastructure increases competition for road space. In turn, there has been a growing emphasis on seeking nag-to-tail approaches to improve the efficiency of urban logistics while minimizing its environmental impact. Like all industries, the way of freight distribution has evolved with technological advancements and digital transformation which have paved a way to embrace new possibilities in optimizing supply chain. It uses real-time and historical data analytics as well as GPS tracking, artificial intelligence (AI), to provide more accurate routing and scheduling of deliveries that helps reduce delivery times for enterprise customers while also delivering significant fuel savings. Some cities have also begun to implement urban consolidation centers, which aggregate freight at the edge of a city area before it enters high-density areas. For example, these centers can help lower the number of cars on the road by reducing traffic and emissions.

Electric vehicles (EVs) are also being used to deliver goods and drones find their place in skies globally transporting goods from fulfillment center to customer or jumpstarting last mile logistics. Public demand and regulations are driving the desire to have more responsible systems for freight distribution. Many of cities have low- or no emission zones, while others charge tolls for driving with polluting vehicles in the city(center) such as London. Additionally, high levels of ambition in the future under new frameworks (e.g. EU and other international bodies targetting greenhouse gas emissions reductions with transport as a key intervention sector). In response, many logistics businesses have begun to implement green technologies and initiatives, from fleets of electric vehicles to solar power for their operations. But the path to green freight delivery is studded with obstacles — from high cost and uneven regulation, all the way to broader infrastructure needs. For instance, the extensive deployment of electric vehicles requires a lot in terms of charging infrastructure which continues to be at embryonic stages even within most developed cities. One of the areas where Urban Planning has lagged far behind is in city infrastructure design which have not been accepting requirements for freight distribution. The success will depend on how these challenges are purged and a well coordinated effort by public sector bodies like transport department, infra providers with private stake holders can make the logistics network sustainable.

Optimising freight routes, schedules and resource allocation to keep costs low and allow for delivery times as short as possible while reducing their environmental impact. The platform can then change its routing decisions on the fly, using live data from such attractions as real-time traffic congestion and delivery emergencies to ensure that deliveries are made fast. In addition, its scalability and flexibility would make it an ideal partner for deployment in a range of urban landscapes as well as integration with existing logistics system. Given the relentless urban growth on global scales and increasingly complex challenges in logistics, solutions such as HMLBP are critical to developing more sustainable and resilient freight distribution systems (Akter & Hernandez 2022; Al-Tarawneh et al. Abstract — This paper presents design issues, experiences and performance assessment of the HMLBP from both theoretical understanding (Hypothesis Testing using Probabilistic Logic Prover- PRLP)and its practical perspective. In a set of simulations as well as real-world case studies, we illustrate how the HMLBP is an effective tool for freight distribution efficiency to reduce operational costs and increase urban mobility. In the end, this HMLBP provides a theoretical and technical innovation for urban logistics researches dealing with growing challenges of Urban Freight Distribution (UFD).

1.1. Problem Formulation. Modern economies depend on urban freight distribution to suit customer and company needs. Urban freight distribution is complicated by congestion, poor road infrastructure, shifting demand, and environmental concerns. To adequately address urban freight distribution concerns, they must be thoroughly defined. To solve the complex urban freight distribution problem, one must first comprehend its numerous facets. Urban areas have a high population density, diverse economic activity, and restricted space (Aszyk et al., 2023; Bassiouni et al., 2024). Due to limits and inefficiencies in freight transportation, expenses rise, delays occur, and environmental impacts emerge.

1.2. Key Challenges:. Several major issues complicate urban freight distribution:

Road congestion: City traffic slows freight vehicles, lengthening delivery times and increasing operational costs.

Lack of infrastructure: Urban road networks that can't accommodate freight traffic cause congestion, bottlenecks, and poor routing decisions.

Delivery to Last Mile: In urban areas, complex delivery routes, limited parking, and time-sensitive delivery windows make "last-mile" delivery more difficult.

Environmental Impacts: Freight distribution worsens urban pollutants, greenhouse gas emissions, and noise pollution.

Change in demand: Urban freight demand is temporally unpredictable, affected by seasonal fluctuations, economic trends, and special events, making it hard to predict and manage.

1.3. Formulating the Problem. The following formulation of urban freight distribution can address these issues:

Objective: The goal is to improve freight distribution efficiency, sustainability, and cost-effectiveness while minimizing congestion and environmental impact.

Limited Access: Problem limits include road capacity, delivery windows, vehicle size and weight restrictions, environmental regulations, and consumer preferences.

Changeable things: Route selection, vehicle scheduling, resource allocation, delivery priorities, and mode choice (truck, train, bicycle, drone) are crucial decision variables.

Standardisation Needs: Finding suitable optimization criteria is crucial to solve the problem. Optimizing customer satisfaction, reducing emissions, maximizing resource use, minimizing delivery time, and reducing road miles are examples.

Technological Integration: Machine learning, IoT sensors, GPS tracking, and real-time data analytics are needed for innovative problem-solving.

To formulate the topic of city freight distribution, one must understand urban logistics' challenges. Traffic congestion, infrastructure restrictions, last-mile delivery issues, environmental concerns, and demand fluctuation must be addressed to improve urban freight distribution. Successful plans and solutions can only then be created. Urban planners, logistics companies, software developers, and government agencies must collaborate to build durable freight distribution networks that can meet modern city demands (Cardona et al., 2021; Castaneda et al., 2021). AI is affecting urban freight distribution as cities worldwide struggle with traffic, environmental deterioration, and wasteful resource utilization. AI can improve urban freight distribution in various ways. AI-powered algorithms can analyze delivery schedules, traffic reports, and road conditions to find the optimum freight distribution routes. Real-time route changes based on delivery priorities and traffic congestion reduce delivery times, fuel consumption, and operational costs via artificial intelligence (AI). AI provides predictive analytics to predict demand, traffic, and delivery restrictions by analyzing prior data and trends (Castrellon & Sanchez-Diaz, 2023). If they can predict demand and traffic, freight operators can better allocate resources, schedule deliveries, and avoid delays. AI allows dynamic scheduling by monitoring and adjusting delivery schedules to real-time events and priorities. In the case of traffic incidents or road closures, fleet management solutions with AI-driven scheduling algorithms help freight operators maximize efficiency and minimize delays. Artificial intelligence can enhance truck scheduling and routing by considering consumer preferences, delivery windows, and fleet capacity (Deveci et al., 2022).

Using AI to allocate vehicles to delivery tasks and optimize delivery sequences reduces empty miles, fuel consumption, and fleet efficiency. AI, particularly computer vision and machine learning, is driving freight autonomous car development. AI-powered navigation systems can enable autonomous delivery cars navigate cities safely and efficiently, reducing human intervention and operational costs. Artificial intelligence adjusts supply and demand for real-time demand-responsive logistics. Optimizing inventory management with AI-driven algorithms that predict consumer demand and adjust distribution strategies can improve customer service and save inventory holding costs for freight operators. AI can reduce the environmental impact of urban freight distribution by improving efficiency and reducing emissions (Ding et al., 2021; Durán et al., 2024; Elalouf et al., 2023). Artificial intelligence systems can analyze environmental data and vehicle telemetry to improve driving efficiency, route optimization, and fuel use. AI is improving urban freight distribution through optimal routes, scheduling, resource allocation, autonomous vehicles, demand-responsive logistics, and reduced environmental impact. AI technology in freight distribution systems will be essential for efficient, sustainable, and resilient urban logistics networks. This will be crucial as cities grow and change. The proposed model has contributed significantly to the development of new approaches to urban planning research and practice:

- This study contributes to the development of a more accurate model for freight distribution in urban areas by allowing for the meticulous customization of the DNN architecture through feature engineering and hyperparameter manipulation.
- The model may be simply adjusted to fit various types of freight distribution in urban areas.
- By incorporating it into freight distribution in urban areas, the Machine Learning model has been utilized to monitor the freight distribution in urban areas in real-time.
- One step closer to the ultimate goal of sustainable urban planning is the model's capacity to assess and improve residential energy consumption.
- Methods for dealing with dynamic and multidimensional data can be advanced with the use of this suggested model, which can forecast urban energy efficiency.

The complete article is organized as follows. section 1 covers the introduction, section 2 covers the related work, section 3 covers the materials and methods, section 4 covers the implementation results and discussion section 5 covers the conclusion and future works.

1.4. Research Contribution. There are the following research contributions as below:

- This paper optimised AdaBoost algorithm for Early Prognosis of Asthma Attack.
- This paper reduce the dangers produced with help of early Prognosis Of Asthma Attack .
- Recognizing and selecting relevant attributes increases the model's capacity to capture crucial patterns and correlations that improve predictive maintenance accuracy.
- The proposed method gains the accuracy to reduce level of medical errors.
- Adopting advanced analytics, machine learning, and optimization technologies improves industry efficiency and competitiveness.

1.5. Paper organization. The complete article is organized as follows. section 1 covers the introduction, section 2 covers the related work, section 3 covers the materials and methods, section 4 covers the implementation results and discussion section 5 covers the conclusion and future works.

2. Related Work. Kayikci (2010) investigates the use of fuzzy-analytical hierarchy process (AHP) and artificial neural networks (ANN) to create a conceptual model for location selection. Optimizing logistics center architecture can boost profitability, ROI, and market share. Aligning with strategic commercial objectives and carefully selecting the location improves urban freight transport networks and supply chain activities. Therefore, before designating a location as a logistics hub, public authorities must thoroughly evaluate this matter's significant economic, social, and environmental impacts. To demonstrate the model's ideas, a numerical example is given. In a stochastic agent-based simulation, Wojtusiak et al. (2012) examine autonomous agent learning theory and practice. The theoretical framework uses the Inferential Theory of Learning, which views learning as a desire for knowledge. The theory is broadened to include approximation and probabilistic learning to meet stochastic learning issues. The practical aspects of autonomous logistics are shown in two use cases: creating prediction models for future environmental conditions and learning inside evolutionary plan optimization.

Abadi et al. (2016) propose a coordinated multimodal dynamic freight load balancing (MDFLB) system to evenly balance rail and road freight loads. The MDFLB system collects and updates data from shipping companies and optimizes cargo loads to available carriers, taking into account current and future network changes. The optimization problem may no longer have the best solution due to freight loads' impact on connection travel times. Iterative strategies, including online network simulation models, address this. Simulation models analyze and develop the optimization-based load balancing solution and predict the optimizer's updated network states. This iterative feedback technique ensures that the cost function declines and stops when it hits a minimum or a predefined stopping threshold, depending on the time frame. A simulated case study of freight distribution in Southern California's two main sea ports shows the efficiency of the proposed coordinated Multi-Destination Freight Location-Based (MDFLB) system.

Adikari and Amalan (2019) investigated how information systems optimize FMCG transportation costs. Information systems should help management operationally and strategically. The study studied operational deployment of an information system using machine learning and big data analytics. Industry specialists and literature examined transportation cost elements, variables, and limits. Next, a Sri Lankan FMCG company's distribution network data is analyzed using a case study. Transportation cost structure was precisely modeled quantitatively. A software model was created to address constraints and cost structure to reduce transportation expenses using big data analytics, machine learning, and computer simulation. To quantify optimization, the generated model was compared to the FMCG producer's transportation model. The proposed model reduces car use to lower transportation expenses. Increased consolidation, route planning, and stacking models achieve this.

Jiang et al. (2019) used a logistic regression model to assess train type and the first registered delay (measured as the relative departure from the timetable). They also used Random Forest "bagging" to extract indirect and sensitive predictors. Training the semi-parametric logistic regression model with 2017 data yielded accuracy and resilience with 2018 data. It handled unanticipated delays like weather during the test period. This study shows that semi-parametric models outperform linear models, Weibull distributions, Binomial logistic regression, and Random Forest. Additionally, the semiparametric model is interpretable and makes accurate predictions with new data.

Pandya et al. (2020) test the model's ability to measure a freight delivery's impact on an Ahmedabad signalized city road's capacity and delay. All-or-nothing is like the highway capacity manual (HCM2010). The goal is to improve understanding of urban freight delivery policy analysis using these methodologies. This study estimates delays and vehicle capacity, taking into account delivery locations, durations, and lane group influences. Support Vector Machine and Artificial Neural Network models predicted vehicle capacity and delays. Results show good agreement between experimental and projected data.

Cardona et al. (2021) propose a case study that collects, cleans, and analyzes rail freight transportation firm public data. The study's objectives are to (i) describe the data using statistical indicators and graphs, (ii) identify patterns related to various Key Performance Indicators, (iii) generate forecasts for these indicators' future trends, and (iv) use the patterns and forecasts to propose tailored insurance products for freight transportation operations.

Akter & Hernandez (2022) used data mining and machine learning to predict a truck's industry based on daily journey and stop sequences using vehicle GPS data. A Weighted Random Forest (WRF) supervised machine learning model predicts agriculture products, mining materials, chemicals, manufactured goods, and miscellaneous mixed commodities. The WRF model predicts 88% accurately and explicitly accounts for class distribution imbalance. Data regarding the fleet, driver, firm, etc. is kept private by the model. We can provide significant insights on the correlation between truck movement and economic (industry) forecasts while protecting data. Our technique predicts freight transit demand using vast truck movement data.

Minbashi et al. (2023) present a machine learning-enhanced macro simulation system to improve yard departure and arrival predictions. The yard departure prediction model uses random forest machine learning. Our yard departure prediction approach is simpler than previous yard simulation methods and has 92% forecast accuracy. A macro simulation network model named PROTON uses departure projections to predict train arrivals at the next yards. We tested this paradigm using data from a segment between two important Swedish yards. The current system outperforms the timetable and a rudimentary machine learning arrival prediction model. The framework had 0.48 R2 and 35 minutes of mean absolute error. We found that examining yard and network interactions can improve complex yard arrival time prediction. This can help yard operators replan yards and infrastructure managers coordinate yard-network activities.

To compare the ARIMA model to qualitative forecasting, Sultanbek et al. (2024) conducted an empirical study. This study uses 2017 data and recognized measurements like MAE and MAPE to prove ARIMA's time series analysis effectiveness. The results confirm the model's efficacy and demonstrate its superiority in improving railway freight demand estimates, notably in Kazakhstan. This research validates methods and advances forecasting procedures that could change railway resource planning. This paper meets current criteria by extending the prediction to 2024. It provides delicate insights for Kazakhstan's railway freight industry's operational and developmental considerations. This expansion places the study in the evolving corporate context, ensuring a thorough and forward-thinking contribution to resource allocation and planning.

Al-Tarawneh et al. (2024) examined commercial vehicle movement trends from 1999 to 2017 using Michi-

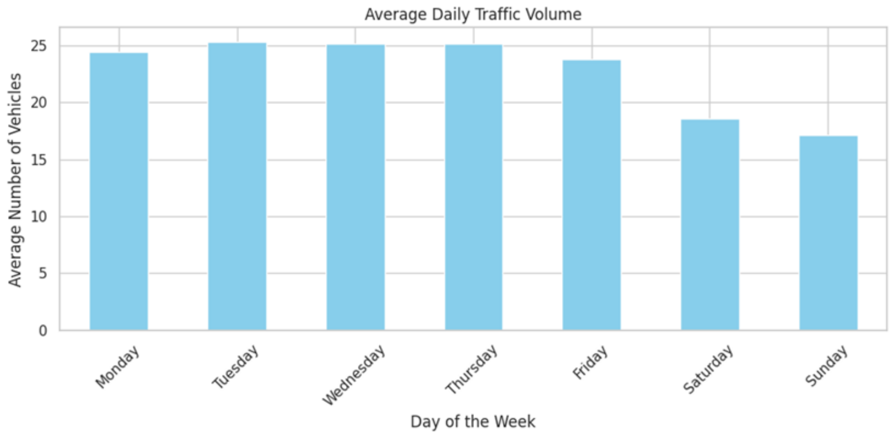

Fig. 3.1: Traffic Volume Daywise

gan commercial vehicle survey (CVS) data from various facilities. This work creates machine learning-based commercial vehicle prediction categories. This study predicts Commercial Motor Vehicle class using Naive Bayes, Linear SVM, and decision tree. A feature selection research determines CMV class prediction criteria. Comparing classification prediction model strategies during training and testing assessed their accuracy. In 89% of cases, the CVS correctly classified commercial autos.

3. Material and Method.

3.1. Dataset. Traffic is getting worse in cities worldwide. Growing urbanization, aging infrastructure, lack of real-time data, and inefficient and disorganized traffic signal scheduling all contribute. There will be severe effects. INRIX, a traffic information and analytics business, projected that U.S. travelers spent $305 billion in 2017 on fuel, time, and product transport in congested areas. Since logistical and economical restrictions prevent cities from building more freeways, they must rethink traffic management. This dataset contains 48.1k (48120) recordings of automobiles passing through four intersections every hour. Fig 3.1 show the traffic volume and impact of weekdays as below below.

Traffic, freight demand, vehicle locations, weather, and delivery schedules are time-series data. We delete missing or inconsistent entries during preprocessing. Interpolation or forward/backward filling can impute missing time-series data. Because anomalies can severely impair the LSTM model's correctness, outlier identification and removal are essential for input data dependability shown in Fig 3.2.

Data normalisation scales all input features to 0–1, speeding up LSTM training. Time-series freight data with kilometers and tons requires this. Feature engineering uses previous demand trends and expected traffic bottlenecks to help the LSTM model predict. Lag features capture temporal interdependence to help the model learn from prior freight trends. Data is split into training, validation, and test sets for LSTM testing. Training using earlier data and verifying and testing later retains data temporal order in timing-based splitting. Sliding windows can provide overlapping sequences to boost training data diversity for LSTM learning in smart cities with dynamic freight distribution. Smart city freight distribution accuracy and efficiency improve using LSTM model input data preprocessing.

4. Proposed Methodology. Urban freight distribution difficulties can dramatically impact logistics efficiency, cost-effectiveness, and sustainability. Urban congestion makes freight vehicles work harder, use more petrol, and cost more. Congestion makes travel time predictions difficult, affecting delivery timetables and customer satisfaction. Freight traffic may surpass urban road network capacity, causing transportation system inefficiencies, bottlenecks, and poor routing decisions. Inaccessible areas with minimal infrastructure make last-mile deliveries harder and longer. In highly populated areas, the "last-mile" of transporting things from distribution facilities to their final destinations can be challenging (Elashmawy et al., 2023; Galambos et al.,

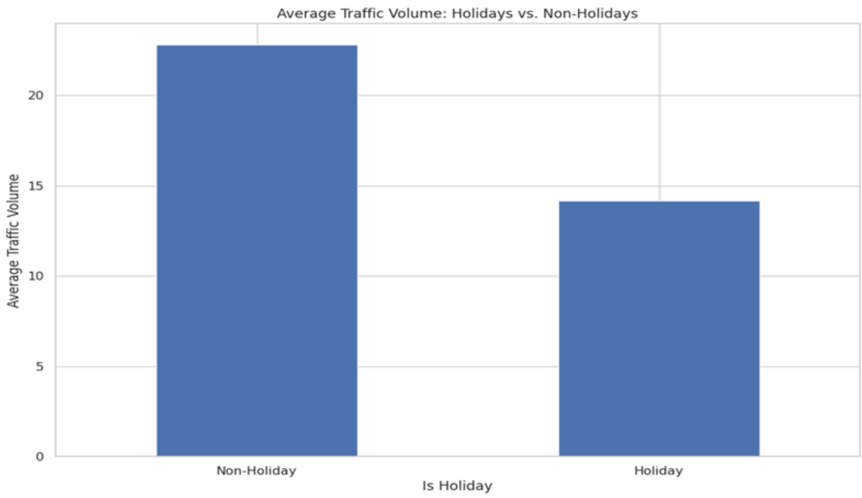

Fig. 3.2: Traffic Volume weekwise

2024; Jia et al., 2020). Delivery vehicles struggle to navigate urban neighborhoods due to small streets, limited parking, pedestrian zones, and congestion. Urban regions have strict parking restrictions and limited freight vehicle space. Because of this, delivery trucks may have problems finding convenient parking for loading and unloading, causing delays and greater operational costs. Urban freight distribution activities create noise, air pollution, and greenhouse gas emissions. We must address these issues to achieve sustainable urban growth, public health, and quality of life. Seasons, economic trends, and special events can dramatically affect urban freight demand volatility and unpredictability.

Managing unpredictability helps meet customer expectations, allocate resources efficiently, and reduce inventory holding costs (Jiang et al., 2019; Johansson et al., 2022; Karam & Reinau, 2022). Urban authorities regulate freight distribution with weight, vehicle size, noise, emission, and delivery time limits. Operations efficiency and regulatory compliance may be tough for logistics organizations. In metropolitan areas, freight vehicles and drivers may encounter theft, vandalism, accidents, and personal safety threats. To protect assets and people, these risks must be avoided and things in transit must be safe. Transportation providers, urban planners, tech businesses, and government agencies must collaborate to address these concerns. Real-time tracking technologies, alternate transportation modes, advanced analytics, and sustainable logistics practices can improve urban freight distribution efficiency, resilience, and sustainability (Kayikci, 2010; Kim & Hong, 2020; Liu et al., 2023).

4.1. Traffic Flow Predictions with LSTM model. Well-managed traffic flows improve urban mobility, congestion, and transportation sustainability. These goals require accurate traffic flow pattern forecast. RNN models with Long Short-Term Memory (LSTM) are now effective at time series prediction challenges like traffic flow prediction. Traffic flow prediction predicts future car traffic on specified roads. Statistics and time series analysis are employed in traditional forecasting. LSTM models excel at capturing nonlinear connections and temporal correlations in traffic data (Machado et al., 2023; Mak et al., 2023; Minbashi et al., 2023; Mjøsund & Hovi, 2022). Long short-term memory (LSTM) models are good for modeling time series data with long-term dependencies because they process and anticipate data sequences well. LSTM neural networks are better at traffic flow prediction than feedforward ones because they have feedback loops that store information over time. To tackle the problem of standard RNNs which are not capable to learn long term dependencies in sequantial data, a new architecture was introduced and it is called as Long Short-Term Memory. Hence, they are widely used in the speech recognition, time series prediction, and natural language processingLong Short-Term Memory (LSTM) networks were introduced by Hochreiter & Schmidhuber (1997). One of the characteristic features is short-term long term memory (LSTM) networks, which remember data in a long-range dependency. These

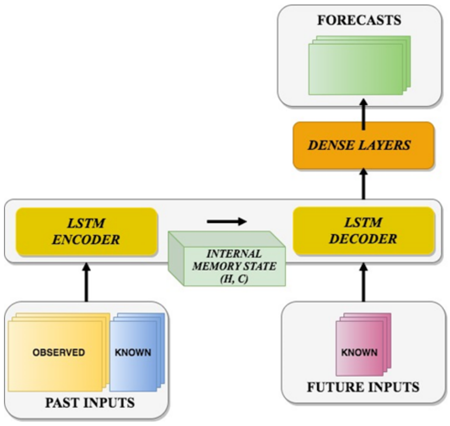

Fig. 4.1: LSTM working

gates, at the cell-level there is a control of flow of information through data and network can preserve or forget it (Mosleh et al., 2023; Nadi et al., 2020, 2022). LSTM have three gates; the input gate, forget gate and output Gate.

- Input gate: Regulates the flow of data into a memory cell.
- Forget Gate: Forget gate decides what to be kept, and what is not useful for the memory cell.
- Output gate: The information from the memory cell goes to output through Output Gate. The inputs are used to decide which memory has got to be erased and added from the respective cells with the help of input gate forgets gate.

These gates activate if the input data matches what the network remembers. Memory cells memorize by retaining cell state. Forget and input gate activations update cell state, allowing the network to remember key facts while flushing away unnecessary ones. The memory cells sends information to the output of network through an output gate. It determines what cell state information should be transferred to the next time period or output. They are specifically suitable for time-series prediction and NLP, speech recognition (example: Apple Siri), LSTM networks can maintain the contextual state of a sequence to aid in finding patterns between elements. The vanishing gradient problem arises when the backpropagation gradients are exponentially tiny (Palmqvist et al., 2022). Unlike most RNNs, this is not a problem for LSTM networks. Moreover, this allows long short term memory (LSTM) networks to remember data and dissipate errors over time. LSTM networks work in one-dimension for time series, two-dimensional image data and three-dimensional volumetric data. Among so many applications of time series prediction, Application 1: Stock price, weather forecasting and power demand etc. used LSTM network widely (Pandya et al., 2019; Saeed et al., 2023) Sahaet al(2007), Shi Zhiyangzhong). Mostly for NLP applications: Language Translation — Sequence-to-Sequence; Sentiment Analysis & Classification, Text Generation tasks use LSTM networks (It actually depends on the type of task you solving though! E.g., in case if accuracy is most important to you than NER networks could be better at some degree too. The long short-term memory (LSTM) networks in applications like virtual assistant, speech-to-text transcription and voice-controlled devices. General-purpose D LSTMs can work for data which is sequece-wise, like in music, captioning and handwriting synthesis. Fig 4.1 depicts the procedure of the proposed methodology below.

Sequential data collected by LSTM networks have transformed the way long-term dependencies in sequences are captured. Their long-term memory and selective processing are useful for time series prediction, NLP, speech recognition etc., (Sultanbek et al.; Taghavi; Tamayo et al.; Tsolaki; Wagner). Long Short-Term Memory (LSTM) network is a specific type of recurrent neural network architecture which was developed to solve the vanishing gradient problem and allow capturing long-term dependencies in sequential data. Below are the steps for working process of LSTM network:-

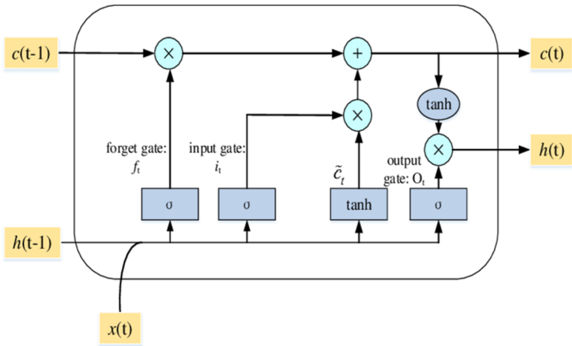

Fig. 4.2: LSTM Gates

4.1.1. Input Processing. At each time step t, the LSTM network receives an input xt representing the input data or features for that time step. These inputs could be numerical values, text embeddings, image pixels, etc. Optionally, the input data can be preprocessed or transformed before being fed into the LSTM network, such as normalization or feature scaling (Wojtusiak et al., 2012).

4.1.2. Gate Calculations. The LSTM network has three types of gates: input gates, forget gates, and output gates. Each gate is responsible for controlling the flow of information within the LSTM cell. Fig 4.2 depicts the various gates in proposed LSTM Model below.

At each time step, the LSTM cell computes the activation at of each gate based on the input xt and the previous hidden state ht-1. The input gate it determines how much new information to store in the cell state shown in figure 4.1. The forget gate ft decides how much information from the previous cell state Ct-1 to forget. The output gate ot regulates how much information from the cell state Ct to pass to the output (Yang et al., 2021; Yuan et al., 2023; Zeng & Qu, 2023).

4.1.3. Cell State Update. The LSTM cell updates its cell state Ct based on the activations of the input gate, forget gate, and candidate cell state. The forget gate ft decides which information from the previous cell state Ct-1 to forget by element-wise multiplication with Ct. The input gate it determines which new information to add to the cell state by element-wise multiplication with the candidate cell state Ct. The cell state Ct is updated by adding the forget gate-modulated previous cell state and the input gate-modulated candidate cell state (Zhang et al., 2023; Zhou et al., 2020)

4.1.4. Hidden State Update. The LSTM cell computes the new hidden state ht based on the updated cell state Ct and the output gate activation ot. The hidden state ht is computed by applying a non-linear activation function (e.g., tanh) to the cell state Ct and multiplying it by the output gate activation ot.

$$h_t = o_t * tanh(C_t) \tag{4.1}$$

The hidden state ht represents the output of the LSTM cell at time step t and can be used for making predictions or passed to subsequent layers in the network.

4.1.5. Recurrence. The LSTM network then proceeds to the next time step t+1 where it computes new hidden state ht and cell state Ct for this timestep, which is done over again with the next input xt+1 and previous hidden state ht. This is iterate for each time step of the input sequence and with that we LSTM learns over long distances; to invest in future prediction or classification from our sequentially dependent data. Efficient long short-term memory (LSTM) is required in prediction, categorization and sequence creation applications.

4.1.6. Autoregressive Approach. Model accuracy, reduction of over fitting and generalizability can be improved by optimizing over parameters such as hyperparameters, network design followed with regularizations. The LSTM models' reliability and robustness improve, making them better at solving complex real-world situations. Optimizing LSTM networks during training speeds convergence, enabling faster model building and deployment. Learning rate scheduling, adaptive optimization methods (like Adam), and batch normalization smooth optimization trajectories to eliminate local minima and expedite convergence to the global optimum. Optimized LSTM models require fewer epochs to achieve performance levels, saving time and computational resources. Optimized LSTM networks resist input data volatility, noise, and adversarial attacks. Optimization uses dropout, L2 regularization, and early halting to avoid overfitting and acquire more broadly applicable representations. As a result, the model can better generalize to new data and handle outliers, improving its reliability and ensuring consistent performance in various real-world situations. LSTM networks must be optimized to handle larger datasets and more complex jobs. Mini-batch training, parallel processing, and model pruning reduce computational overhead and memory needs for training larger models on limited hardware. Optimised LSTM models in production provide real-time inference and system integration.

Algorithm 1 Algorithm for Learning Rate Scheduling Optimization in LSTM

Start
Initialize LSTM network architecture and hyperparameters (e.g., number of layers, number of units, learning rate, etc.).
Preprocess input data (e.g., normalization, standardization, etc.).
Split data into training, validation, and testing sets.
Initialize the learning rate schedule parameters (e.g., initial learning rate, decay rate, patience, etc.).
Train the LSTM network:
a. For each epoch:
i. Train the network using the current learning rate and training data.
ii. Validate the network performance using the validation data.
iii. If the validation loss does not improve for a predefined number of epochs (patience), decrease the learning rate according to the learning rate schedule.
iv. Repeat steps i-iii until convergence or a maximum number of epochs is reached.
Evaluate the trained LSTM network on the testing data to assess its performance.
End

This algorithm outlines the steps involved in training an LSTM network with learning rate scheduling optimization. Learning rate scheduling adjusts the learning rate during training based on predefined criteria, such as the validation loss not improving for a certain number of epochs, to improve convergence and prevent overfitting. The WOA is a nature-inspired metaheuristic optimisation method that mimics humpback whale hunting. Sayedali Mirjalili and Andrew Lewis presented this algorithm in 2016 to solve optimisation challenges in engineering, computer science, and logistics. The WOA algorithm simulates humpback whale bubble-net feeding and exploration and exploitation. Whales use bubble-net feeding to trap their prey, illustrating the algorithm's exploitation strategy. Whales can explore new search spaces during the exploration phase, preventing the algorithm from being stuck in local optima. WOA is popular for its simplicity, ease of implementation, and ability to find optimal or near-optimal solutions. Given its balance between exploration and exploitation, it is ideal for high-dimensional and difficult optimisation issues. The approach is versatile and converges well, making it appropriate for function optimisation and machine learning hyperparameter tuning. WOA uses humpback whale behaviours to solve difficult optimisation problems, and its integration with machine learning models like LSTM networks can improve logistics, resource management, and predictive analytics performance.

Exploration and humpback whale hunting are combined by WOA. WOA avoids local optima, which can improve global solutions in optimisation issues. WOA is simpler and has fewer control parameters than PSO and Genetic Algorithms. Its simplicity makes integration into our LSTM framework easy and computationally efficient. Previous research show that WOA outperforms numerous optimisation methods in benchmark functions and applications. This performance illustrates its longevity and reliability, making it suitable for machine learning hyperparameter optimisation. Application to many issue domains is another reason to choose WOA. WOA's adaptability enhances optimisation, model accuracy, and efficiency in smart city freight distribution, where data is dynamic and complicated. Modern WOA research has shown good results in similar applications, supporting our decision.

Algorithm 2 LSTM Hyperparameter Optimization with Whale Optimization Algorithm (WOA)

Input:
- Freight distribution dataset
- LSTM hyperparameter search space (learning rate, batch size, number of layers, etc.)
- WOA parameters: population size, iterations, exploration rate

Result:
- Optimized LSTM hyperparameters for efficient freight distribution prediction

Step 1. Initialize WOA population with random LSTM hyperparameter sets
Step 2. Evaluate initial fitness of each whale using LSTM model accuracy on validation data
for iteration = 1 to N do
for each whale (bat) do
- Update position of whale based on exploration and exploitation phase
- Train LSTM model with updated hyperparameters
- Evaluate fitness (model accuracy) on validation dataset
- If better fitness is achieved:
- Update whale's position (hyperparameters)

end for
- Update whale positions using best solution found so far
- Adjust exploration/exploitation balance based on iteration number

end for
Step 3. Return best hyperparameters (learning rate, batch size, number of layers, etc.)
Step 4. Train final LSTM model with optimized hyperparameters on full dataset Step 5. Evaluate performance on test data to ensure generalization

Table 5.1: Feature importance with coefficient values

S. No.	Component	equipment
1	Processor	Multi-core CPU (Intel Core i7)
2	RAM	Minimum 16 GB
3	Storage	SSD with at least 500 GB space
4	Operating System	Ubuntu 20.04 / Windows 10
5	Python Version	Python 3.8 or higher
6	Deep Learning Framework	TensorFlow 2.x or PyTorch

5. Results and Discussion. Strong hardware is needed to optimize hyperparameters and implement the LSTM model with Whale Optimization Algorithm (WOA) on large datasets. A multi-core CPU like Intel Core i7 or AMD Ryzen 7 can handle simpler models, while a GPU like the NVIDIA RTX 2080 or above is suggested for complex LSTM network training. The GPU processes LSTM matrix operations faster, accelerating model training for smart city freight distribution time-series data. We recommend 32 GB RAM for larger datasets for smooth model training and WOA optimizations. Medium data sets need 16 GB. SSDs speed up loading large datasets and saving model checkpoints. Table 1 lists possible model experiments.

5.1. Simulation result. Strong hardware is needed to optimize hyperparameters and implement the LSTM model with Whale Optimization Algorithm (WOA) on large datasets. A multi-core CPU like Intel Core i7 or AMD Ryzen 7 can handle simpler models, while a GPU like the NVIDIA RTX 2080 or above is suggested for complex LSTM network training. The GPU processes LSTM matrix operations faster, accelerating model training for smart city freight distribution time-series data. We recommend 32 GB RAM for larger datasets for smooth model training and WOA optimizations. Medium data sets need 16 GB. SSDs speed up loading large datasets and saving model checkpoints. Table 5.1 lists possible model experiments.

The finest deep learning frameworks, TensorFlow or PyTorch, have efficient LSTM model implementation and optimization packages. WOA can be optimized with NumPy and SciPy Python applications. GPU

Table 5.2: Simulation Parameters for LSTM with Whale Optimization Algorithm (WOA)

S. No.	Parameter	Range	Optimized Value
1	Learning Rate	0.0001 – 0.01	0.001
2	Batch Size	16 – 128	64
3	Number of LSTM Layers	1 – 4	2
4	Number of Units per Layer	50 – 500	200
5	Dropout Rate	0.1 – 0.5	0.3
6	Epochs	50 – 500	200

acceleration of TensorFlow or PyTorch requires CUDA and cuDNN. Development IDEs like Jupyter Notebook, PyCharm, or VSCode are helpful, and Matplotlib and Seaborn help analyze model tuning and optimization results. Table 5.2 lists Whale Optimization Algorithm (WOA) range and optimal LSTM simulation parameters.

Smart city freight distribution jobs require LSTM model simulation settings using the Whale Optimization Algorithm (WOA) for high predictive accuracy. Model performance depends on LSTM hyperparameters such learning rate, batch size, layers, and units per layer. For fast convergence without overshooting minima, the learning rate is optimized to 0.001, updating model weights per iteration. Increased 64-batch size ensures accurate gradient changes without memory overload. The model captures complicated temporal correlations in freight data with 2 LSTM layers and 200 units per layer. Important WOA parameters include whale population size and iterations are 50 and 100. With these parameters, solution space search is computationally light. Exploration and exploitation are balanced at 1.5, enabling the algorithm explore the hyperparameter search area. After moderate improvements, the convergence threshold of 0.001 stops optimization, preventing overfitting and wasted computation. LSTM freight distribution and smart city efficiency improve with these values.

Traffic flow prediction are essential for transportation system optimization, road safety, and congestion reduction. Traffic managers can avert problems via adaptive signal control, real-time issue management, and dynamic routing with accurate forecasts. Traffic flow estimations aid infrastructure and urban planning decisions. Recently popular RNNs include long short-term memory (LSTM) models. Sequential data patterns and linkages are easily detected by these models. Traffic flow data has dynamic and non-linear correlations, making long short-term memory (LSTM) models better than time-series forecasting. After learning past traffic patterns, LSTM models can accurately forecast future traffic.

Authors created training, validation, and testing datasets. The training set trains a model, the validation set fine-tunes hyperparameters and tracks training progress, and the testing set evaluates the final model's performance and scales or normalizes data. After that, they train the suggested LSTM model with the training dataset. The loss function on the training and validation sets is compared to check for overfitting or underfitting. After executing the proposed LSTM, the traffic prediction are being made and compared with true value shown. Fig 5.1 depicts the Traffic Prediction Vs True values below.

Following training, the model is evaluated on the testing dataset. The authors compare the model's anticipated and real traffic flows to examine how well it detects data patterns and variations, using metrics like MAE, MSE, RMSE, etc. They explore why actual values diverge from projections. The root mean squared error of the proposed model is 0.23912122600654664. The MAE is 0.17255859883764077. Fig 5.2 demonstrates the traffic volume over Time with anomalies.

Fig 5.3 shows LSTM freight distribution RMSE and standard deviations. The baseline model, with an RMSE of 11.67 $\pm$ 8.17, is a benchmark for LSTM architectural improvements. A little increase in accuracy is observed with the first direct LSTM model, with an RMSE of 11.28 $\pm$ 8.34. However, higher standard deviation indicates greater performance variability. A similar RMSE of 11.30 $\pm$ 8.16 indicates slight gains in the autoregressive LSTM model, but no significant outperformance over the baseline.

Encoder-Decoder LSTM topologies improve performance considerably. The Direct LSTM Encoder-Decoder model effectively reduces error with an RMSE of 10.55 $\pm$ 7.83 compared to baseline and simple models. This shows the Encoder-Decoder technique better captures freight distribution temporal dynamics. The autoregres-

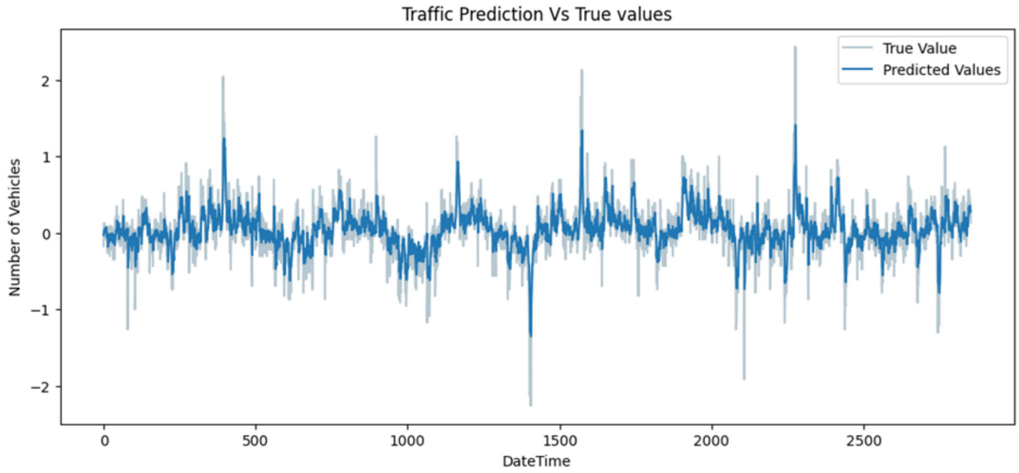

Fig. 5.1: Traffic Prediction Vs True values

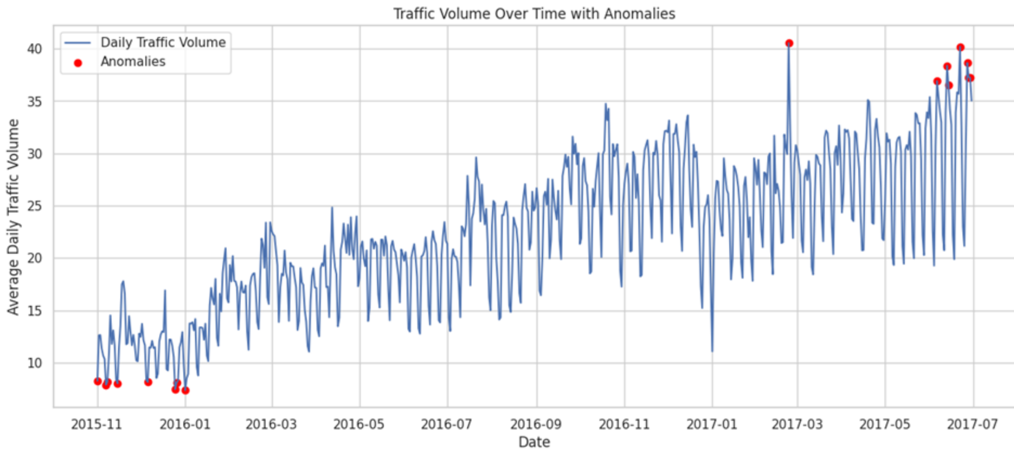

Fig. 5.2: Traffic Volume over Time with anomalies.

sive LSTM Encoder-Decoder model surpasses the baseline but has a lower RMSE of 11.08 ± 8.11 compared to its direct counterpart. Direct LSTM Encoder-Decoder is the most accurate, making it best for smart city freight distribution prediction. Fig 5.4 compares LSTM models' MAE and standard deviation to a baseline freight distribution performance prediction model. The baseline model's MAE is 7.25 and standard deviation is 5.18, making it a good LSTM architecture benchmark.

Direct LSTM improves on baseline but increases forecast variability with an MAE of 7.03 and a standard deviation of 5.36. PAE is 7.12 and SD is 5.32 for the AutoRegressive LSTM model, improving marginally over baseline. Performance improves further using Encoder-Decoder models. Direct LSTM Encoder-Decoder has the lowest MAE of 6.58, indicating high accuracy. A lower standard deviation of 4.95 signifies more consistent forecasts. The AutoRegressive LSTM Encoder-Decoder model has an MAE of 6.94 with a standard deviation of 5.26, outperforming the baseline with more variability. Encoder-Decoder models, especially the Direct LSTM, are most accurate and consistent for freight distribution projections.

The Whale Optimisation Algorithm (WOA)'s computational costs come from iterativeness and objective function complexity. WOA computes the objective function several times based on population size and max-

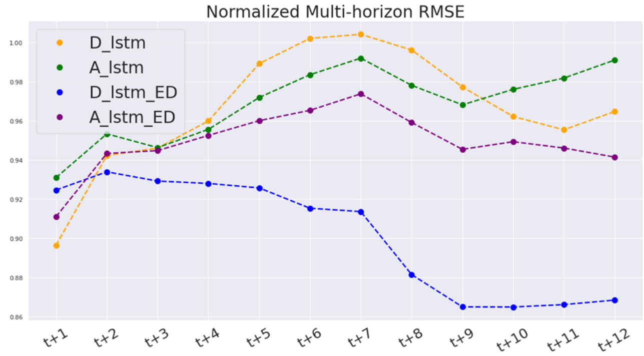

Fig. 5.3: Normalised RMSE metric

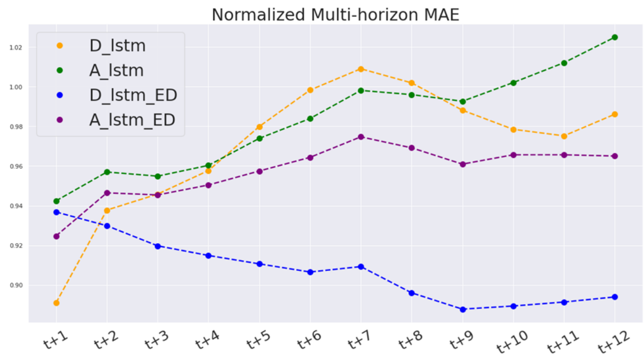

Fig. 5.4: Normalised MAE metric

imum iterations to evaluate solution fitness. The computational work needed to evaluate the fitness function increases with the number of elements to optimise, increasing time complexity. Real-time smart city logistics and resource management require quick decisions. WOA optimisation also requires resource consumption. Although memory-efficient, WOA may need a lot of resources, especially for large-scale optimisation problems with enormous datasets. Memory and processor speed affect algorithm performance, especially with high-dimensional datasets utilised in smart city applications. WOA with advanced models like LSTMs may demand additional computational resources, restricting its use in energy-efficient and computing-intensive applications. WOA needs algorithm optimisation for real-time smart city use. Combining WOA with other optimisation algorithms or parallel processing reduces computational costs. Surrogate models can approximate the goal function to hasten convergence without compromising solution quality. These computational challenges can be solved to apply WOA for real-time smart city decision-making, boosting operational efficiency, resource consumption, and system performance.

Due to their ability to capture long-term dependencies, long short-term memory (LSTM) networks are ideal for sequential data. Traditional approaches struggle to forecast sequential data patterns like traffic flows, demand fluctuations, and resource availability in logistics and smart city contexts due to temporal dependencies. These applications have widely used LSTMs for sequential modelling. By learning from historical data, LSTMs help logistics predict demand patterns, optimise supply chain operations, and improve route planning. LSTM models can optimise route options and reduce delays by anticipating traffic congestion, fuel consumption, and delivery times for goods distribution. By projecting resource demands and consumption trends, LSTMs help smart cities manage traffic, resource allocation, and energy usage. Smart transport applications, where anticipating traffic patterns or energy usage can improve city planning and service efficiency, benefit from their temporal dependency modelling. Two aspects determine the WOA-optimized model's scalability: WOA's convergence efficiency in high-dimensional search spaces and its computational footprint while processing bigger data quantities. Since its exploration-exploitation balance avoids local minima and converges efficiently, WOA is adaptable to huge datasets. WOA can dynamically change the search process due to its iterative nature, which is useful when training with large datasets. We also explore how distributed processing can manage the model's computing requirements, which could be valuable for smart city logistics data with enormous volumes. These tactics keep the WOA-optimized LSTM model resilient and efficient, making it suitable for large-scale goods delivery.

The Whale Optimisation Algorithm (WOA) has balanced accuracy and processing speed for smart city real-time operations. Complex calculations, iterations, and objective function evaluations make exact models computationally expensive. Dynamic goods routing and real-time resource allocation require quick judgements, slowing processing. Thus, maximising solution correctness while limiting computational needs for fast operational responses is problematic. Model complexity increases with precision, requiring greater processing resources. Smart city efficiency and sustainability may limit resources, making simulations impractical. Even minor accuracy improvements may increase calculation time and resource utilisation in huge data or high-dimensional parameter sets. In real-time systems, precision alone might delay results, slowing operations. Practitioners may use multiple ways to balance accuracy and computing efficiency. With less resources and processing time, simplified or approximation models can solve problems. Parallel or distributed processing accelerates optimisation without losing accuracy. Greedy heuristics or machine learning reduce computation times and maintain accuracy in WOA hybrid models. A robust foundation for fast, accurate decision-making simplifies smart city logistics.

5.2. Discussion. Whale Optimisation Algorithm (WOA) provides various benefits for optimising logistics processes, however it may have drawbacks that limit its suitability in diverse logistics scenarios and urban contexts. Limitations include its dependence on the optimised objective function. WOA excels at continuous and differentiable functions but struggles with extremely non-linear, discontinuous, or multimodal functions. WOA's usefulness in logistics applications like freight distribution and route optimisation might be limited by traffic patterns, vehicle capabilities, and demand changes. If the objective function does not match the algorithm's assumptions, inferior solutions may occur, limiting its applicability in many logistical settings. Other limitations include the algorithm's exploration-exploitation balance.

WOA tries to balance researching new ideas with leveraging good ones, but it sometimes favours one over the other. The system may perform poorly in dynamic metropolitan areas with fast changing logistics needs, such as real-time traffic circumstances or unanticipated demand spikes. Due to excessive exploitation or failure to explore the solution space, WOA may be unable to adapt to changing logistical requirements, making it less responsive and inefficient. Additionally, WOA scalability in large-scale logistics applications raises concerns. As cities grow and logistical networks become more complicated, the number of viable solutions to examine might skyrocket, increasing computation times and resource needs. WOA's iterative nature may slow down solutions for large fleets, many delivery sites, or complex routing, especially when quick decision-making is needed. This shortcoming may hinder its use in high-demand applications that require agility and response.

Finally, urban features can affect WOA's performance. Population density, infrastructural quality, and service demand variations affect how successfully the algorithm optimises logistics operations. WOA may work better in urban settings with predictable demand and well-defined patterns than in chaotic environments with unpredictable traffic and delivery needs. Thus, WOA may need to be customised to each logistics scenario, such as by adding local traffic data or other optimisation methods, to be more effective in varied urban contexts.

6. Conclusion and Future Scope. We developed a model to anticipate future traffic conditions using past data to aid traffic management and city planning. We found our LSTM model promising for traffic flow prediction. We achieved [performance metrics], proving the model can discover patterns and dependencies over time. Features' value in predicting traffic flow was established by feature importance analysis. This new understanding will help us improve our models and data use. The model accurately depicted traffic flow's weekly and daily trends and the impact of weather and special events. LSTM is a black-box model that works but is hard to understand. Transparency and model decision explanation methods need more research.

In smart cities, Whale Optimisation Algorithm (WOA) freight allocation minimises resource consumption and emissions, boosting sustainability. Logistics efficiency improves route planning and load optimisation, decreasing fuel and greenhouse gas emissions. WOA helps logistics companies reduce their carbon footprint by locating the optimum distribution lines and scheduling deliveries to minimise bottlenecks. In cities where traffic and inefficient goods activities cause pollution, this optimisation is essential. By linking logistics to environmental goals, WOA for goods allocation improves smart city quality of life and sustainable urban mobility.Optimised products allocation saves businesses and communities money and helps the environment. Improving transportation efficiency and fuel costs can enhance revenues and save customers money. Streamlining operations and controlling resources reduces labour and vehicle maintenance costs. Logistics optimisation can extend road life and cut maintenance costs. WOA in goods logistics boosts smart city sustainability and economic resilience, benefiting the environment and economy.

The input data must be high-quality and fine-grained for reliable traffic flow calculations. Incomplete data, missing values, and erroneous reporting can cause bias or model failure. LSTM models are computationally intensive and require lots of resources for training and inference. Scalability and efficiency are essential for large-scale deployments and real-time applications.

Our technique worked well on this dataset, but it may not work in other places or times. The model's adaptability needs more exploration. LSTM architecture can be improved via hyperparameter tweaking, regularization, and ensemble methods to make more accurate and resilient predictions. Better integration to traffic camera feeds, mobile trends and infrastructure. That would greatly increase the systems understanding of current state (FFS) as well. Smooth sailing from there. LSTM models can be interpretable and trustworthy by using modification of attention mechanisms, feature visualization and model-agnostic explanation strategies. Implementation might be simplified by exploring deployment of a real-time traffic flow prediction model. For example, low-latency inference optimization and integration with our downstream traffic control system. Based on previous line of thought, our study demonstrated traffic flow prediction with LSTM models and expressed neural networks can be an assistance in understanding the patterns related to urban mobility such as congestion scenario which has a direct relation with policy favouring actions. While our results are encouraging, further research and novel ideas need to be explored in order take full advantage of predictive analytics for transportation management.

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