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Optimization of Istanbul Urban Traffic Data with Grey Wolf Optimization-Assisted Machine Learning Techniques: Comparative Analysis of Long Short-Term Memory and eXtreme Gradient Boosting

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ABSTRACT

This study examines machine learning approaches enhanced by the Grey Wolf Optimization (GWO) algorithm for analyzing Istanbul's complex urban traffic patterns. The GWO was employed due to its capability to efficiently handle complex nonlinear traffic patterns and its robustness in achieving global optimization, outperforming several conventional metaheuristics. Using hourly traffic density data from June–December 2024 obtained from Turkey's Ministry of Environment database, researchers developed a Unified Traffic Density Index combining average speed (40%), vehicle count (40%), and speed variation (20%) to identify the busiest traffic zones. The dataset was obtained from the Ministry of Environment, Urbanization, and Climate Change and covers the period from June 1, 2024, to December 31, 2024. The dataset contains hourly data for 2462 geohash regions within the boundaries of Istanbul province. The methodology compared long short-term memory (LSTM) and eXtreme Gradient Boosting (XGBoost) algorithms using both standard and GWO-optimized hyperparameters. Time series analysis separated trend, seasonality, and randomness components while examining hourly and daily periodicity patterns in traffic data. Results demonstrated that GWO optimization significantly enhanced both algorithms' performance. The standard LSTM model's systematic deviations and wave-like patterns were substantially reduced through GWO optimization. The XGBoost performed consistently in both versions, with the GWO-XGBoost combination achieving superior prediction accuracy. Performance metrics revealed that GWO-XGBoost attained the lowest mean squared error (1.6209) and mean absolute error (0.9082) values while achieving the highest coefficient of determination (R^2 percentage bias = ±0.8486%, outperforming other configurations. These findings indicate that the GWO-XGBoost combination shows significant potential as a highly accurate solution for traffic density prediction applications for traffic management systems within critical high-density zones of metropolitan areas like Istanbul, particularly for traffic density prediction applications. The study concludes that advanced optimization techniques are essential for addressing traffic management challenges in rapidly urbanizing cities with increasing vehicle density.

Index Terms— Gray wolf optimization, smart cities, traffic density forecasting

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I. INTRODUCTION

Rapid urbanization and vehicle density are presenting urban transport systems with unprecedented challenges. This transformation threatens the efficiency and sustainability of transport infrastructure, necessitating a re-evaluation of traffic management processes. With its strategic location connecting Europe and Asia, Istanbul has an extremely complex and dynamic traffic structure due to its unique spatial structure and demographic characteristics. Therefore, the limited solution possibilities offered by traditional traffic analysis approaches are insufficient, especially in detecting multi-layered patterns and unexpected anomalies in large-scale urban networks. This situation necessitates the development of analysis methods with advanced computational power and flexible modeling capabilities.

Although this study focused on Istanbul, the proposed methodology is designed with adaptability in mind. The Grey Wolf Optimization (GWO)-based optimization framework can be readily applied to other metropolitan areas by recalibrating the traffic density index components (average speed, vehicle count, speed variation), normalization ranges, and peak-period multipliers according to local traffic conditions. For example, in cities like London, Tokyo, or São Paulo, traffic dynamics differ substantially due to variations in infrastructure, cultural driving behavior, and peak-hour patterns. Thus, the flexibility of the framework ensures that the approach remains generalizable across diverse urban environments, while still retaining city-specific calibration for accurate modeling.

In recent years, the integration of optimization algorithms into traffic analysis processes has emerged as a rising research area in academic circles. In this context, the GWO algorithm, developed by drawing inspiration from social structures and hunting strategies in nature, offers an innovative approach that demonstrates superior performance compared to traditional methods, particularly in feature selection problems. However, studies on the application of the GWO algorithm to the analysis of urban traffic data are still quite limited, and this area remains largely unexplored.

The rapidly increasing rate of urbanization and the parallel rise in vehicle density are making urban transport systems increasingly complex and difficult to manage. As a megacity connecting Europe and Asia, Istanbul has unique traffic dynamics due to its distinctive geographical and demographic structure. Effectively analyzing this complex structure requires sophisticated approaches that go beyond traditional traffic analysis methods. Traditional methods often fail to adequately detect the multidimensional patterns and unexpected anomalies that emerge in large-scale urban networks, making the use of advanced computational techniques inevitable in this field.

In this context, the integration of optimization algorithms with traffic analysis processes has been at the center of growing research interest in recent years. The GWO algorithm was developed based on the social organization and hunting strategies of grey wolves and achieves higher success rates than traditional approaches, particularly in feature selection problems. However, the use of this algorithm in the analysis of urban traffic data has not yet been sufficiently explored in the literature.

Traffic analysis approaches commonly used today have various structural and functional limitations. In particular, the computational load encountered in the analysis of high-dimensional feature spaces makes the practical application of these methods difficult. Additionally, their capacity to detect fine-scale traffic anomalies occurring in real time is limited. It is often not possible to comprehensively identify patterns in traffic data across different time scales such as hourly, daily, weekly, and seasonal. Furthermore, the integration of optimization algorithms with traffic engineering has not yet been sufficiently developed.

This study aims to enable more efficient and accurate analysis of traffic data through a feature selection framework developed based on the GWO algorithm. In this context, the objective is to identify patterns in traffic flow on hourly, daily, weekly, and seasonal scales. In addition, a robust anomaly detection method will be established by evaluating the results obtained from different data sources in a consensus-based manner. The ultimate goal of the study is to obtain applicable analysis outputs that will contribute to urban traffic management and to establish a repeatable methodological structure for smart city applications based on these outputs.

This research makes an important contribution by providing a rigorous comparative analysis of GWO-assisted optimization on both long short-term memory (LSTM) and eXtreme Gradient Boosting (XGBoost) models for this complex, real-world traffic dataset. The work methodically evaluates the impact of GWO on these distinct architectures for both feature selection and hyperparameter tuning. In addition, a new consensus-based anomaly detection framework is proposed, and a comprehensive methodology is being developed that will enable the systematic analysis of traffic data at multiple scales. The developed approach is validated under real-world conditions using Istanbul city traffic data, and the outputs obtained in this context are made available to the research community as open source.

II. LITERATURE REVIEW

A. The Importance and Challenges of Traffic Data

Traffic data is a critical component in understanding and managing urban mobility. It provides insights into traffic flow, congestion patterns, and the overall performance of transportation networks. In the context of Istanbul, traffic density data has been used to develop predictive models for traffic congestion forecasting [1]. This data is essential for planning and optimizing traffic management strategies, reducing congestion, and improving the efficiency of transportation systems. Additionally, real-time traffic data enables the development of smart city applications such as mobile apps that provide citizens with accurate traffic information and alternative route suggestions [2]. The importance of traffic data is further emphasized by its role in supporting advanced traffic information systems. These systems rely on data from various sources, including sensors, cameras, and floating cars, to provide real-time information to travelers. This information helps users make informed decisions about their journeys, reducing travel time and fuel consumption [3, 4]. Despite its importance, traffic data presents various challenges. One of the primary challenges is the complexity of processing large volumes of data from various sources. This includes data from sensors, GPS, and other IoT devices that must be processed and analyzed in real time to provide accurate and reliable information [5]. Another challenge is the integration of data from different sources, which requires robust data fusion techniques to ensure consistency and accuracy [3]. Additionally, traffic data is often influenced by external factors such as weather conditions, special events, and accidents, which can introduce variability and unpredictability into traffic models. This makes it challenging to develop models that can accurately predict traffic congestion and other anomalies [2].

B. Traffic Characteristics in Istanbul

These challenges are particularly evident in large and densely populated cities. Istanbul, Turkey's largest metropolis, with its complex traffic structure and variable dynamics, increases the difficulty of such analyses; therefore, an in-depth examination of Istanbul's traffic characteristics is essential for the development of city-specific strategies. Istanbul is one of the world's most populous cities, with over 16 million inhabitants. The city's traffic characteristics are influenced by its unique geography, which spans two continents connected by bridges, and its rapid urbanization. High population density and an increasing number of private vehicles have led to severe traffic congestion, particularly on the bridges connecting Europe and Asia [6, 7]. Traffic density in Istanbul varies significantly throughout the day. For example, traffic density is low during the early morning hours (00:00–07:00), with accuracy levels reaching up to 93%

under low-density conditions [1]. However, during peak hours, traffic congestion becomes a major issue, particularly on bridges and at major intersections. The high rate of private vehicle ownership, which accounts for 25% of all vehicles in Turkey, exacerbates the problem [6]. The impact of traffic congestion in Istanbul is significant. It results in longer travel times, higher fuel consumption, and reduced productivity. Additionally, traffic congestion contributes to environmental pollution, and Istanbul experiences high levels of carbon emissions and air pollution [6, 7].

C. The Role of Anomaly and Pattern Analysis in Urban Management

In this context, traditional methods alone are not sufficient for modeling and managing Istanbul traffic; advanced data processing techniques such as anomaly and pattern analysis must be used. These analyses play an important role in identifying unusual situations in urban transport and revealing patterns in traffic behavior. Anomaly detection is a critical component of traffic management systems. It involves identifying unusual patterns or events in traffic data that deviate from normal conditions. These anomalies may include unexpected congestion, accidents, or other disruptions that affect traffic flow. Various methods have been proposed for anomaly detection, including machine learning techniques such as support vector machines and k-nearest neighbor algorithms [8]. An innovative approach to anomaly detection involves the use of spatio-temporal hypergraph convolutional neural networks. This method models the road network as a hypergraph, capturing the spatial and temporal relationships between different road segments. This approach has been shown to perform better than traditional methods in detecting rare anomalies and understanding their propagation across the network [9]. Pattern recognition is another important aspect of traffic data analysis. It involves identifying recurring patterns in traffic data, such as daily commuting patterns, seasonal changes, and other periodic trends. These models can be used to predict future traffic conditions and optimize traffic signal control strategies [6, 10] Machine learning techniques such as LSTM networks and transformer models have been successfully applied to traffic prediction tasks. For example, it has been shown that transformer models can capture complex patterns in traffic data to provide accurate traffic predictions [2]. Anomaly and pattern analysis plays a crucial role in urban management by enabling proactive traffic management. Traffic managers can respond to disruptions in real time, reduce the impact of congestion, and improve overall traffic flow by identifying anomalies and recognizing patterns. Additionally, model analysis can inform long-term planning and policy decisions, such as the implementation of congestion pricing schemes and low-emission zones [6, 7]. The integration of anomaly and pattern analysis with other technologies, such as Internet of Things (IoT) sensors and big data analytics, further enhances the effectiveness of urban traffic management. These technologies provide a comprehensive view of traffic conditions, enabling more accurate predictions and better decision-making [6, 11]. Traffic data is a vital resource for understanding and managing urban mobility. Challenges associated with traffic data, such as processing large volumes and integrating data from multiple sources, must be addressed in order to realize its full potential. Istanbul's unique traffic characteristics, including its high population density and geographical constraints, make it a challenging case study for traffic management. However, anomaly and pattern analysis applications supported by advanced technologies such as machine learning and IoT sensors offer promising solutions for reducing traffic congestion and improving urban mobility. By leveraging these tools, city planners and policymakers can develop more effective strategies for managing traffic in Istanbul and other cities around the world. Powerful optimization techniques are required to perform such analyses efficiently.

D. Grey Wolf Optimization General Outline

In recent years, algorithms inspired by nature have provided effective solutions in this field. In this context, the GWO method has produced remarkable results, particularly in complex problems such as anomaly detection and pattern extraction.

The GWO algorithm is a meta-heuristic method inspired by the social behavior and hunting strategies of grey wolves. Its theoretical developments have significantly influenced engineering and computer science, particularly in optimization problems. The GWO's simplicity, few parameters, and ability to balance exploration and exploitation make it a versatile tool in various fields. The following sections summarize the basic theoretical foundations and advances of GWO. The GWO mimics the pack dynamics of grey wolves, where alpha, beta, and delta wolves lead the search for solutions and establish a framework for social interaction-based optimization [12]. The algorithm uses mathematical models that simulate the hunting process, enabling an effective exploration of the solution space [13]. Recent variants such as Attention Mechanism–based GWO enhance exploration by adaptively weighting the influence of leader wolves, thereby increasing convergence speed and solution quality [14]. The GWO has been hybridized with other algorithms to enhance its robustness and applicability in complex optimization scenarios [15]. The GWO has been successfully applied in fields such as computational fluid dynamics, machine learning, and environmental engineering, demonstrating its versatility and effectiveness in solving real-world problems [3]. While GWO holds significant promise, challenges such as local optimum stagnation and slow convergence persist.

The structural characteristics of the GWO algorithm, particularly the balance it provides between the exploration and exploitation processes, offer powerful solution potential for high-dimensional and dynamic problems such as traffic data. These advantages make GWO more effective and flexible when compared to traditional methods.

The GWO has demonstrated significant advantages in various fields, particularly in engineering and computer science. Its meta-heuristic nature enables effective problem solving in optimization tasks, making it a valuable tool in these fields. The following sections summarize its specific benefits. The GWO has been successfully applied to classical engineering design problems by demonstrating its ability to effectively solve complex optimization tasks [16].

Variants such as the hybrid GWO improve convergence performance and balance exploration and exploitation, thereby increasing its applicability in real-world engineering scenarios [17].

In computer science, GWO has been integrated with machine learning models such as XGBoost to develop malware detection systems. This combination has demonstrated GWO's effectiveness in security applications, achieving high accuracy and recall rates [18]. Modified versions of GWO, such as Group-based Synchronous-Asynchronous GWO, enhance population diversity and adaptability, leading to better performance in various optimization problems [19].

The inclusion of memory and evolutionary operators in GWO variants further addresses issues such as early convergence, making it more robust for various applications [20]. While GWO shows promise, it is important to consider that its effectiveness may vary depending on the specific problem context and optimization environment, and that careful algorithm selection and tuning are required. Recent studies [21, 22] highlight optimization frameworks for traffic prediction in Istanbul and comparable megacities.

A new hybrid LSTM model integrated with the Improved Harris Hawks Optimization (IHHO) algorithm has been developed for river flow estimation. The results show that the LSTM-IHHO model outperforms the standalone LSTM and other hybrid optimization models in all statistical metrics, providing more accurate and reliable predictions. The importance of the Willmott Index (WI) and percentage bias (PBIAS) metrics is emphasized [23, 24].

This study aims to systematically apply the GWO for feature selection and hyperparameter optimization in urban traffic analysis. The primary contribution of this work is the systematic application and comparative evaluation of GWO for optimizing machine learning models (LSTM and XGBoost) on a novel, high-resolution Istanbul traffic dataset. This includes the validation of a new Unified Traffic Density Index and an assessment of the performance gains achievable in this specific complex urban environment.

III. MATERIAL AND METHOD

A. Material

In this study, hourly traffic density data for Istanbul for the period June–December 2024, obtained from the ULASAV Traffic Density Database belonging to the Ministry of Environment, Urbanization and Climate Change of the Republic of Turkey [25], was used to assess traffic density and identify the most congested geographical areas. Data analysis was conducted based on geographical location (geohash) subdivisions, and traffic density identification was supported by multi-faceted criteria. Fig. 1 shows the traffic density values in all geohash areas on the Istanbul map in the data set, represented as a heat map.

Table I contains statistical information about the dataset under the heading Descriptive Analysis of Vehicle Speed and Volume Geospatial Data. Dataset of over 11.5 million records reveals traffic patterns within a tightly concentrated geographical area, as indicated by the low variance in latitude and longitude coordinates. The average vehicle speed shows a relatively symmetric distribution around 56.5 km/h, while the wide range between minimum and maximum speeds—from standstills (0 km/h) to high velocities (255 km/h)—illustrates fluctuating traffic conditions ranging from congestion to free-flowing movement. The number of vehicles per record displays a highly right-skewed distribution, with a median of 58 but a high mean of 106, pulled upward by extreme values (up to 1684 vehicles), highlighting significant variability and the presence of high-traffic hotspots amidst generally moderate volume locations.

In this study, geohash encoding was applied to ensure spatial granularity of the traffic data. A 6-character geohash precision was employed, which provides an adequate balance between spatial accuracy and computational efficiency. Neighboring geohash regions were aggregated based on average traffic density values, enabling coherent representation of urban zones. It is worth noting that higher geohash precision levels may yield finer spatial resolution but at the cost of increased computational overhead, whereas lower levels may result in loss of local traffic variability.

First, traffic density was assessed using speed-based indicators. Speed variance and speed ratio were calculated based on average speed, maximum, and minimum speed values, and a normalized congestion index was defined according to the legal speed limit within the city. Through these indicators, it was accepted that low speed and low speed variation indicate high traffic density.

In the second stage, a vehicle count-based analysis was performed. For each geohash, the total number of vehicles, average number of vehicles, and observation frequency were evaluated, and

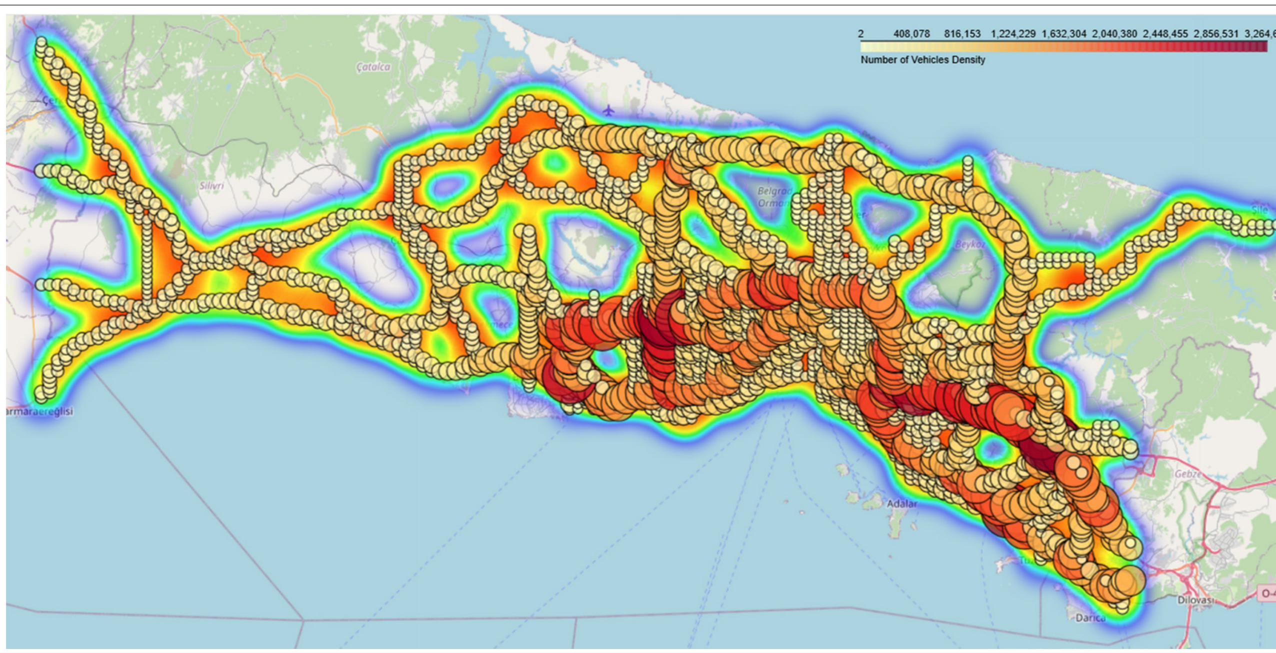

Fig. 1. Geohash heatmap on the Istanbul map in the data set.

TABLE I. DESCRIPTIVE ANALYSIS OF VEHICLE SPEED AND VOLUME GEOSPATIAL DATA

	Latitude	Longitude	Min_Speed	Max_Speed	Ave_Speed	Numb_vehıc
Count	11506936	11506936	11506936	11506936	11506936	11506936
Mean	41,06300314	28,88716931	22,8664	101,7942	56,5456	106,1255
Std	0,100941184	0,356864373	24,3140	37,0309	25,9909	133,7867
Min	40,76751709	27,96569824	0	1	1	1
25%	40,99822998	28,6907959	3	72	33	21
50%	41,05865479	28,93249512	10	101	54	58
75%	41,13006592	29,15222168	42	130	80	137
Max	41,34429932	29,63562012	207	255	207	1684

the average number of vehicles per unit time was compared with regional density.

In the third stage, the proposed combined traffic density index (CDTI) was calculated. This index comprises three main components: low average speed (40% weight), high vehicle count (40% weight), and low speed variation (20% weight). All these parameters were standardized using Min-Max normalization, and a traffic density score was created based on their weighted averages.

Fourthly, traffic density was supported by time-based analysis. Using the time stamps in the data set, hourly and weekly patterns were identified, and a time-weighted multiplier was defined for periods such as the start/end of working hours and weekends. This allowed traffic during peak hours to be represented more meaningfully.

The obtained traffic density scores were categorized into meaningful categories, and each region was classified as "Low," "Medium," "High," or "Very High." The highest traffic density was observed in the geohash region with the highest score according to the relevant traffic density index.

As a result, it was determined that the multi-criteria approach provides the most accurate density measurement; in particular, the "Combined Traffic Density Index (CDTI)" which evaluates average speed, vehicle density, and speed variation together, was recommended as the most effective method. Additionally, time-weighted evaluation more accurately models the variability of traffic flow during the day and on weekdays/weekends. To validate the 40%–40%–20% weighting for the CDTI, several alternative weighting combinations (e.g., 60/20/20, 33/33/33, 20/40/40) were tested. The 40/40/20 split provided the most stable and accurate performance, minimizing the MSE of the final GWO-XGBoost model. The results of this analysis are presented in Table II

B. Method

The geohash region with the highest traffic value was determined based on the CDTI defined above. This location was marked on the map in the visual analysis section of the study and presented Fig. 2 as the point with the highest traffic congestion in the spatial context.

The average speed data for the relevant geohash region was separated into time series components, and the trend, seasonality, and randomness elements were examined in detail. In this analysis, presented in four sub-panels on the graph, the general time series at the top was separated into the following components.

Reflecting long-term changes over time, this component shows that the average speed exhibits weekly fluctuation patterns, with significant declines observed in some periods. This may indicate seasonal traffic increases or slowdowns due to road/infrastructure issues. A highly pronounced periodic structure is observed on an hourly basis. This structure reflects daily recurring traffic patterns (e.g., increased congestion during morning and evening hours). The data exhibits strong hourly seasonality. This component, which represents random changes outside of trend and seasonal effects, shows various deviations spread over time. These deviations may be associated with unforeseen traffic events (accidents, sudden road closures, etc.).

Fig. 3 analysis provides an important foundation for understanding the temporal patterns of traffic flow in the geohash region in question.

1) Data Processing:
Prior to model training, all input features were normalized to the [0,1] range using Min-Max scaling to prevent bias caused by differences in feature magnitude. Missing values were processed using a strategy of filling them in based on the previous hour Last Observation Carried Forward (LOCF). To validate this choice, this method was compared against linear interpolation. The resulting difference in the final model MSE was negligible (<1%), confirming the suitability of the computationally simpler LOCF method for this high-frequency data. Additionally, feature engineering was performed to capture

TABLE II. MODEL PERFORMANCE COMPARISON FOR DIFFERENT CTDI WEIGHTING SCENARIOS

Scenario	Weighting	Model Performance (Test Set MSE)
Alternative 1	20%, 40%, 40%	0.192
Alternative 2	33%, 33%, 33%	0.205
Alternative 3 (Recommended)	40%, 40%, 20%	0.174
Alternative 4	50%, 25%, 25%	0.218
Alternative 5	60%, 20%, 20%	0.226

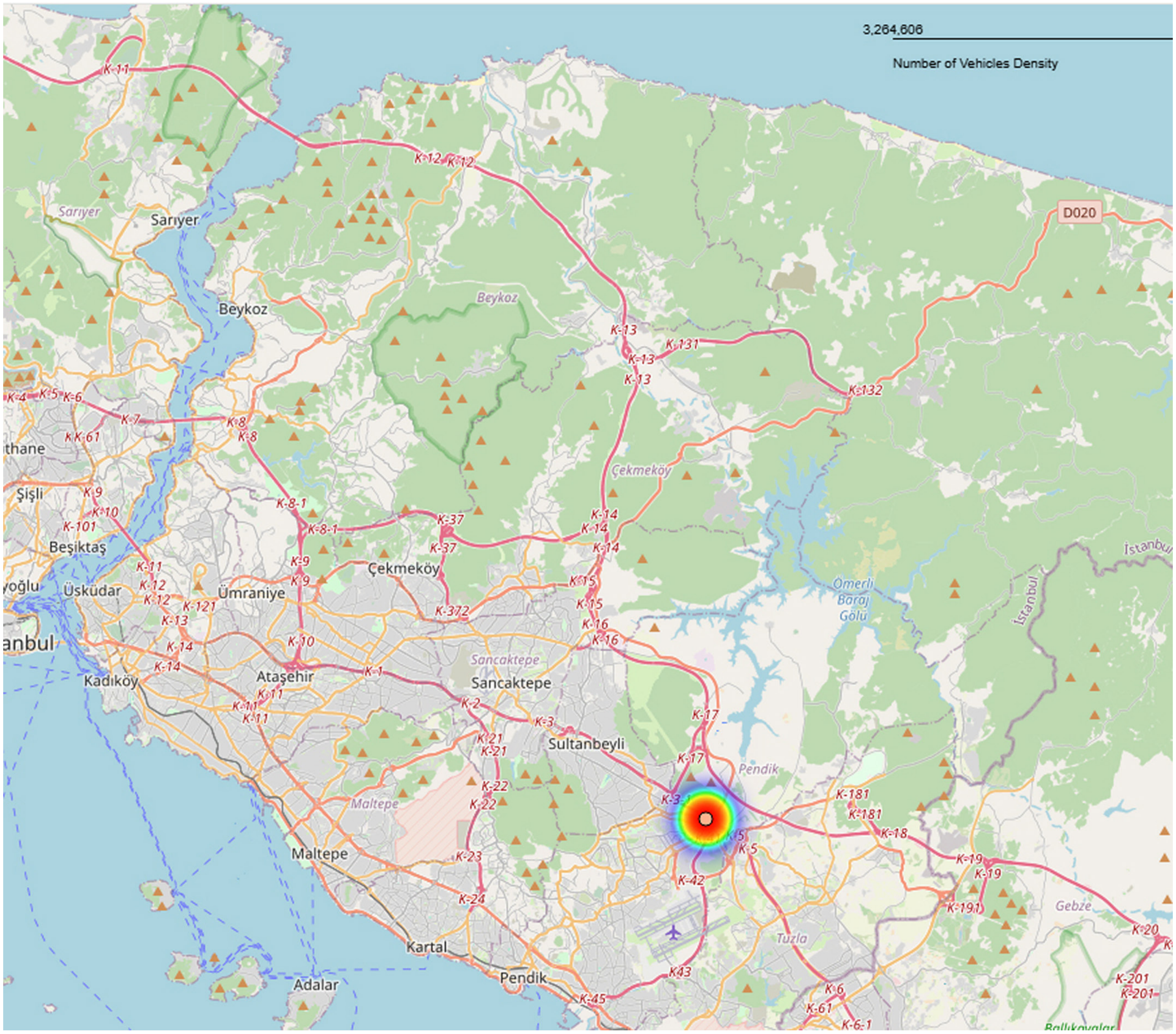

Fig. 2. The geohash region with the highest traffic density index.

sequential dependencies. This included time-delay (lag) features (e.g., average_speed at t-1, t-3, and t-6 hours; vehicle_count at t-1 hour) and temporal features (e.g., hour_of_day, day_of_week, and a binary "is_weekend" flag).

Traffic anomaly detection has been examined in greater detail to address irregularities such as accidents, unexpected events, or sudden increases in the number of vehicles. The GWO's adaptive discovery mechanism enables the identification of data points that deviate significantly from normal traffic patterns and can be considered anomalies. To contextualize this feature, the conceptual framework was compared with outlier detection approaches such as statistical thresholding and interquartile range and extracted from the dataset. While traditional methods offer simplicity and speed, detection enhanced with GWO demonstrates greater adaptability in capturing complex and dynamic urban anomalies. Future work may focus on the hybrid integration of GWO-based anomaly detection models for greater robustness.

2) Model Training:

The dataset was split into training (70%), validation (10%), and test (20%) subsets. To increase generalizability and actively monitor for overfitting, a five-fold cross-validation strategy was adopted during training. The validation loss was observed during training to ensure the model was not overfitting to the training data. The models' hyperparameters were optimized using the GWO, which increases both convergence speed and prediction accuracy.

3) Validation and Performance Metrics:

Model performance was evaluated using root mean squared error, mean absolute error (MAE), and the coefficient of determination (R^2). These metrics were chosen to comprehensively assess both the accuracy and the explanatory power of the models.

4) Long Short-Term Memory:

Long short-term memory networks are an architecture developed to overcome the limitations of traditional Recurrent Neural Networks in modeling long-term dependencies. The LSTM units use cell state and

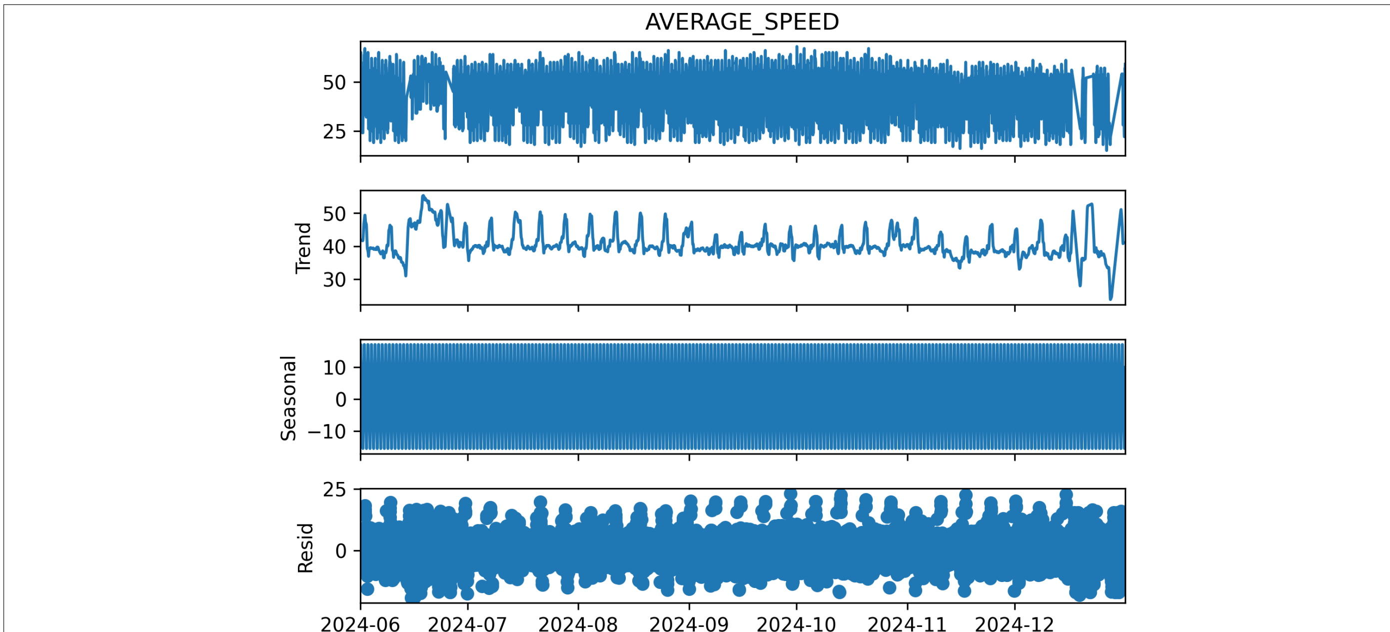

Fig. 3. The selected geohash seasonal decomposition plot.

three types of gate mechanisms to learn sequential dependencies in time series data: forget gate, input gate, and output gate. These structures determine how much information to remember, how much to update, and how much to output.

The forget gate determines which information should be discarded from the previous cell state as (1):

$$f_t = \sigma\left(W_f \cdot \left[h_{t-1}, x_t\right] + b_f\right)\#(1)(1)$$

The input gate controls which new information should be stored in the cell state through two components shown as (2), (3):

$$i_t = \sigma\left(W_i \cdot \left[h_{t-1}, x_t\right] + b_i\right)\#(2)(2)$$

$$\widetilde{C_t} = \tanh\left(W_C \cdot \left[h_{t-1}, x_t\right] + b_C\right)\#(3)(3)$$

The cell state is updated according to (4):

$$C_t = f_t \odot C_{t-1} + i_t \odot \widetilde{C_t}\#(4)(4)$$

Finally, the output gate determines which parts of the cell state should be output, shown as (5) and (6):

$$o_t = \sigma\left(W_o \cdot \left[h_{t-1}, x_t\right] + b_o\right)\#(5)(5)$$

$$h_t = o_t \odot \tanh\left(C_t\right)\#(6)(6)$$

This structure prevents gradients from decaying over time, enabling the learning of longer contexts. The LSTMs are particularly effective for sequential data-focused problems such as time series prediction, natural language processing, and financial data analysis.

5) eXtreme Gradient Boosting:

The XGBoost is an ensemble learning algorithm that optimizes the gradient boosting method and stands out for its high accuracy and processing speed. XGBoost offers a structure based on decision trees that minimizes errors iteratively. The basic principle is that successive models learn from the errors of previous models to reduce the overall prediction error.

Mathematically, the model's output is $\widehat{y_i} = \sum_{k=1}^{K} f_k\left(x_i\right)$, $f_k \in \mathrm{F}$ consists of decision trees, and F denotes the entire space of possible decision trees. The objective is to minimize the following regularized objective function shown as (7):

$$\mathrm{L}(\phi) = \sum_{i=1}^{n} l\left(y_i, \widehat{y_i}\right) + \sum_{k=1}^{K}{}' \left(f_k\right)\#(7)(7)$$

Here, l is the loss function (e.g., squared error), $\Omega\left(f\right) = \gamma T + \frac{1}{2}\lambda\left|w\right|^2$ is the regularization term that controls model complexity. The optimal tree is derived at each iteration using a second-order Taylor expansion. This prevents overfitting and improves overall accuracy. The XGBoost is widely used in various regression, classification, and ranking problems due to its tolerance for missing data, parallel computing capability, and special regularization techniques.

6) Grey Wolf Optimization:

Grey Wolf Optimization is a heuristic optimization algorithm that mathematically models the hunting strategies of grey wolves while searching for the best solution in the solution space. The basic mechanism of GWO is based on the principle of surrounding the prey (the optimal solution) and eventually attacking it. This behavior is simulated in the algorithm by updating the omega (ω) positions of other individuals based on the position information of the alpha (a), beta (β), and delta (δ) individuals.

Mathematically, a wolf's position is updated as (8) and (9):

$$\vec{D} = \left|\vec{C} \cdot \vec{X_p}\left(t\right) - \vec{X}\left(t\right)\right|\#(8)(8)$$

$$\vec{X}\left(t+1\right) = \vec{X_p}\left(t\right) - \vec{A} \cdot \vec{D}\#(9)(9)$$

Where, $\overrightarrow{X_p}(t)$ represents the positions of the leader wolves (α, β, δ). $\vec{A}$,$\vec{C}$ represents, the adaptive vectors that manage the balance between exploration and exploitation. These vectors are defined as (10), (11):

$$\vec{A} = 2 \cdot \vec{a} \cdot \vec{r_1} - \vec{a} \#(10)(10)$$

$$\vec{C} = 2 \cdot \vec{r_2} \#(11)(11)$$

where $\vec{a}$ is a control parameter that linearly decreases from 2 to 0 over the iteration, $\vec{r_1}$,$\vec{r_2}$ are random vectors in the range [0, 1]. This structure enables GWO to dynamically switch between exploration and exploitation, thereby increasing its effectiveness in converging to the global optimum.

Alpha, beta, and delta are the best members of the pack, so they understand the location of the prey (optima) better. Therefore, during the hunt, these wolves lead the search process, and omega wolves adjust their positions according to the positions of the three most suitable wolves in the pack, as shown in (12)-(15).

$$\overrightarrow{D_{-}} = \left|\overrightarrow{C_1} \cdot \overrightarrow{X_{-}} - \vec{X}\right|, \overrightarrow{X_1} = \overrightarrow{X_{-}} - \overrightarrow{A_1} \cdot \overrightarrow{D_{-}} \#(12)(12)$$

$$\overrightarrow{D_{\dagger}} = \left|\overrightarrow{C_2} \cdot \overrightarrow{X_{\dagger}} - \vec{X}\right|, \overrightarrow{X_2} = \overrightarrow{X_{\dagger}} - \overrightarrow{A_2} \cdot \overrightarrow{D_{\dagger}} \#(13)(13)$$

$$\overrightarrow{D_{.}} = \left|\overrightarrow{C_3} \cdot \overrightarrow{X_{.}} - \vec{X}\right|, \overrightarrow{X_3} = \overrightarrow{X_{.}} - \overrightarrow{A_3} \cdot \overrightarrow{D_{.}} \#(14)(14)$$

$$\vec{X}(t+1) = \frac{\overrightarrow{X_1} + \overrightarrow{X_2} + \overrightarrow{X_3}}{3} \#(15)(15)$$

IV. RESULTS AND DISCUSSION

This section presents the results of the average speed estimation study conducted on the traffic data set in detail. In the study, LSTM and XGBoost algorithms were evaluated using both standard hyperparameters and parameters optimized with GWO. Model performances were visually compared through correlation analysis between actual and predicted values and time series prediction graphs.

Fig. 4 shows the prediction performance of the Standard LSTM model. The most notable feature of this graph is that the data points show a systematic deviation around the ideal prediction line ($y = x$). A distinct wave-like pattern is observed in the 25–35 and 45–55 speed ranges. This indicates that the LSTM model tends to produce systematically high or low predictions in certain speed ranges.

The distribution of data points in the LSTM graph exhibits a heterogeneous structure, and it is observed that the prediction errors do not have a constant variance (heteroscedasticity problem). The model performs relatively better at low speed values (20–30) and high-speed values (50–60) but exhibits significant deviations at medium speed values.

Fig. 5 presents the performance of the Standard XGBoost model. Compared to LSTM, this model's predictions show a much more homogeneous and consistent distribution around the ideal line. Data points are positioned close to the ideal prediction line across the entire speed range (15–60) and exhibit a clear linear relationship.

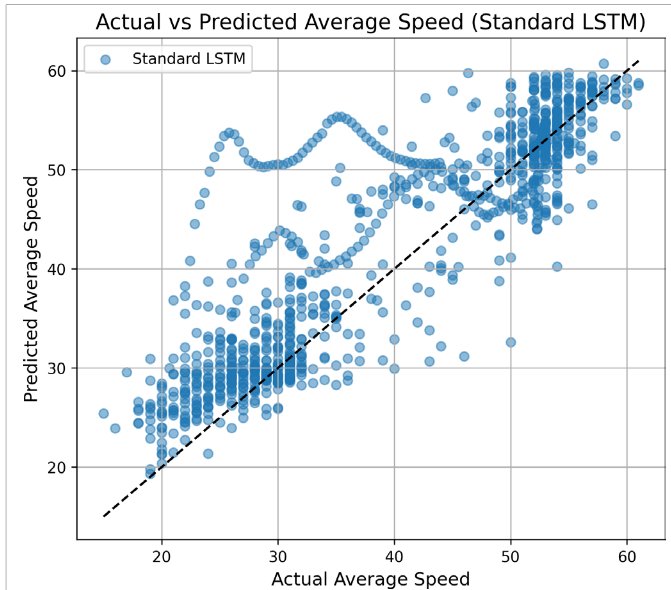

Fig. 4. Average speed prediction performance of LSTM algorithm.

Homogeneous variance (homoscedasticity) is observed in the XGBoost model, and prediction errors are randomly distributed. This indicates that the model performs consistently across all speed ranges and does not contain systematic errors.

The performance difference between the two models is quite significant. The XGBoost model demonstrates superior prediction accuracy and consistency compared to LSTM. Although the LSTM model is strong in modeling temporal relationships, the ensemble learning approach of XGBoost produced more effective results for this specific data set.

The model demonstrates homogeneous variance. Critical analysis shows consistent accuracy across all speed ranges, with minor

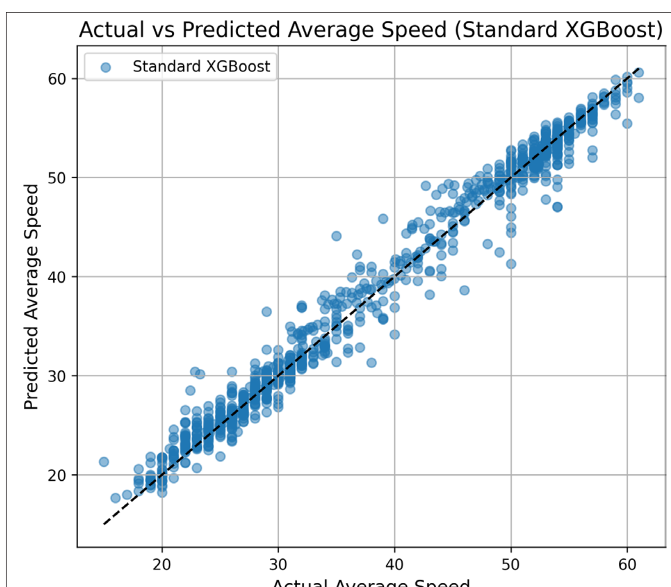

Fig. 5. Average speed prediction performance of XGBoost algorithm.

deviations at low speeds. The XGBoost algorithm is considered a preferable approach for speed prediction problems, as it demonstrates lower prediction error, higher model reliability, and less systematic bias.

The hyperparameters of both models were optimized using the GWO algorithm, and performance improvements were evaluated. GWO optimization was applied to achieve an optimal balance between model complexity and prediction accuracy. Table III shows the parameters of the standard and hyperparameter-tuned models.

The GWO algorithm itself was configured with a population size of 30 agents and set to run for 50 iterations, balancing computational cost and solution quality. The hyperparameter search space used by GWO for both LSTM and XGBoost models is detailed in Table IV.

Figs. 6 and 7 show the performance of the LSTM and XGBoost models optimized with GWO. Significant performance improvements were observed in both models after optimization.

Fig. 6 shows the performance of the LSTM model optimized with GWO. Although significant improvements are observed compared to the standard LSTM version, some systematic characteristics still exist. It has been found that data points form specific patterns and tend to deviate from the ideal line in the 25–35 km/h and 40–50 km/h ranges.

The GWO optimization has significantly reduced the wave-like systematic deviations in the LSTM model but has not eliminated them. The model demonstrates more consistent performance at low-speed values (15–30 km/h) and high-speed values (55–60 km/h) but still exhibits a heterogeneous distribution in the mid-speed ranges. This may be due to the complexity of modeling temporal dynamics in the LSTM.

Fig. 7 shows the performance of the XGBoost model optimized with GWO. When examining the distribution of data points around the ideal prediction line ($y = x$), a high level of correlation and consistency can be observed. The model demonstrates homogeneous performance across the entire 15–60 km/h speed range, with data points tightly clustered along the ideal line.

Following GWO optimization, the variance structure of the XGBoost model has improved significantly, and its homoscedasticity property has been strengthened. The random distribution of prediction errors indicates that the model does not contain systematic errors and produces reliable predictions across all speed segments. The tight clustering observed at high speed values (50–60 km/h) indicates that the model's prediction capacity in this range has been optimized.

The performance difference between the two optimized models has become more pronounced compared to their standard versions. The GWO-XGBoost model showed superior prediction accuracy and model stability after optimization, while the improvement rate in the GWO-LSTM model remained limited.

When evaluated in terms of the R^2, the GWO-XGBoost model is seen to have a higher explanatory power. From the perspective of residual analysis, the error terms of the XGBoost model show a more normal distribution, while certain patterns are still present in the LSTM model.

The effect of the GWO algorithm on the two models differs. For XGBoost, the optimization process further improved the already high performance and increased model reliability. For LSTM, optimization significantly reduced the obvious problems in the standard version but could not eliminate some characteristics inherent in the algorithm.

In conclusion, the GWO-XGBoost combination is considered the optimal solution for the traffic speed prediction problem in terms of both prediction accuracy and model stability.

In the GWO-LSTM model, the systematic deviations observed in the standard version have been significantly reduced, and the distribution of data points around the ideal line has become more uniform. In the GWO-XGBoost model, the already high performance has been further improved, and prediction accuracy has been increased.

As shown in Fig. 8, when examining the time series prediction performance of the GWO-LSTM model, significant improvements in the model's ability to capture temporal dynamics are observed after GWO optimization. Graphical analysis reveals that the optimized LSTM model successfully tracks the general trend structure of actual speed values during the test period from November 22, 2024 to January 1 2025. The model is particularly effective at capturing long-term speed changes and seasonal patterns, but it exhibits a certain degree of smoothing effect in short-term volatility and sudden speed fluctuations. The GWO optimization has improved the memory gate parameters of the LSTM, enabling it to model temporal dependencies more consistently and significantly reducing the lagged prediction problem. However, the model still cannot fully capture the amplitude of real values in high-frequency speed changes, and its prediction capacity remains limited, especially for extreme values (below 20 km/h and above 60 km/h). Overall, the GWO-LSTM combination demonstrates satisfactory performance in traffic speed prediction and offers a suitable solution for practical applications. The optimized LSTM captures long-term patterns effectively but exhibits smoothing in short-term fluctuations.

TABLE III. MODEL PARAMETERS

		Model Parameters
Standard	LSTM	LSTM Units = 64, Dropout Rate = 0.2
	XGBoost	Learning Rate = 0.1, n_estimators = 100
Hyperparameter optimized	GWO-LSTM	LSTM Units = 169, Dropout Rate = 0.15, Learning Rate = 0.01000, Batch Size = 29
	GWO-XGBoost	Learning Rate = 0.143, Max Depth = 5, n_estimators = 393, subsample = 0.67, colsample_bytree = 1.00, min_child_weight = 10

TABLE IV. GWO HYPERPARAMETER OPTIMIZATION SEARCH SPACE

Parameter	Model	Search Space Range
LSTM Units	GWO-LSTM	[50, 200]
Dropout Rate	GWO-LSTM	[0.1, 0.4]
Batch Size	GWO-LSTM	[16, 64]
n_estimators	GWO-XGBoost	[100, 500]
Max Depth	GWO-XGBoost	[3, 10]
Learning Rate	GWO-XGBoost	[0.01, 0.2]

Fig. 9 shows the performance of the GWO-XGBoost model in predicting traffic speed. When comparing the actual average speed values (blue line) with the model predictions (orange line) for the last two months of 2024, the model generally performs well. There is a high correlation between model predictions and actual values until the first half of December, but it is noteworthy that model predictions deviate from actual values in some periods from the middle of December onwards. These deviations are particularly noticeable at low-speed values (in the 20–30 km/h range), and it is observed that the model's prediction accuracy decreases in these ranges. Toward the end of the year, the model's prediction performance improves again and better captures the actual values.

To evaluate the behavior of model performances over time, time series graphs of predictions made on the test data were created. These graphs provide a visual means of evaluating the models' ability to adapt to dynamic traffic conditions and the consistency of their predictions.

Fig. 10 shows the time series prediction performance of the Standard LSTM, Standard XGBoost, GWO-LSTM, and GWO-XGBoost models, respectively. Figure is retained because it highlights differences

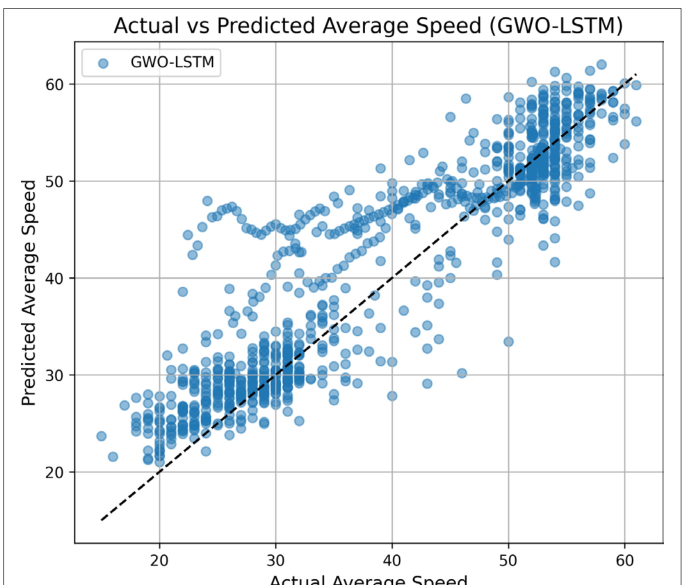

Fig. 6. Average speed prediction performance of GWO-LSTM algorithm.

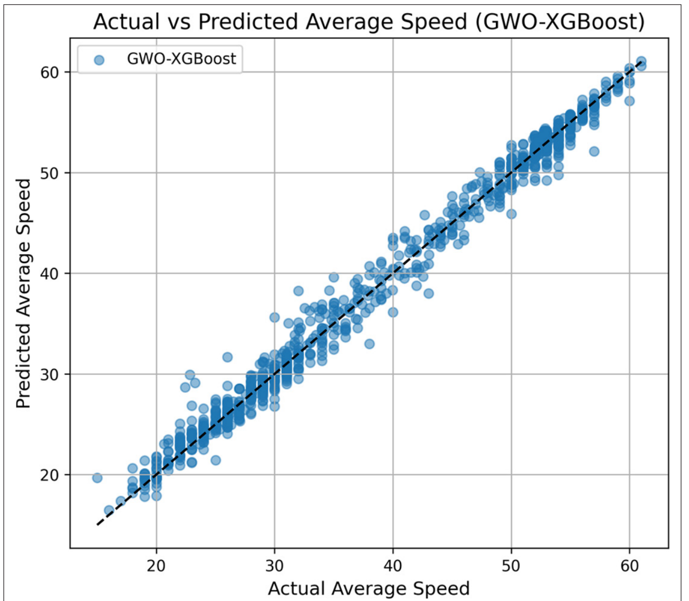

Fig. 7. Average speed prediction performance of GWO-XGBoost algorithm.

between baseline and optimized models. Scientific explanation added regarding temporal dynamics. Time series analyses reveal that GWO optimization improves prediction consistency for both algorithms and enhances model stability against sudden changes. It has been observed that optimized models produce more reliable predictions during time periods when traffic density is variable.

Table V provides a comparative summary of the performance metrics of all models used in the study. The evaluation criteria used were MSE, MAE, R^2 WI. The WI measures the graded fit of the model to the observed values between 0 and 1; the closer it is to 1, the more perfect the model is. PBIAS: Shows the direction and severity (in %) of the model's systematic deviation from the observations; the closer it is to 0, the more unbiased the model is.

The numerical data presented in Table V is visually supported by the comparative performance graph in Fig. 11. The model performance comparison presented in Fig. 11 shows the evaluation of different machine learning algorithms in terms of three basic performance metrics. The graph compares the performance of ARIMA, Standard XGBoost, GWO-XGBoost, Standard LSTM, and GWO-LSTM models using MSE, MAE, and R^2 values. The analysis results reveal that GWO optimization provides significant performance improvements for both algorithms. When evaluated in terms of the XGBoost algorithm, GWO optimization resulted in an approximately 33% decrease in the MSE value and a similar improvement in the MAE value. The increase in the R^2 value indicates that the explanatory power of the model has improved. The effect of GWO optimization is even more dramatic in the LSTM algorithm. The standard LSTM model's relatively high MSE value (41.2812) decreased significantly to 29.0507 after the GWO-LSTM application. This clearly demonstrates the effectiveness of the GWO algorithm in optimizing LSTM hyperparameters. When evaluating overall performance, the GWO-XGBoost combination demonstrates superior performance with the lowest error rates (MSE and MAE) (1.6209 and 0.9082) and the highest explanatory coefficient (R^2) (0.9896). These findings emphasize the critical importance of

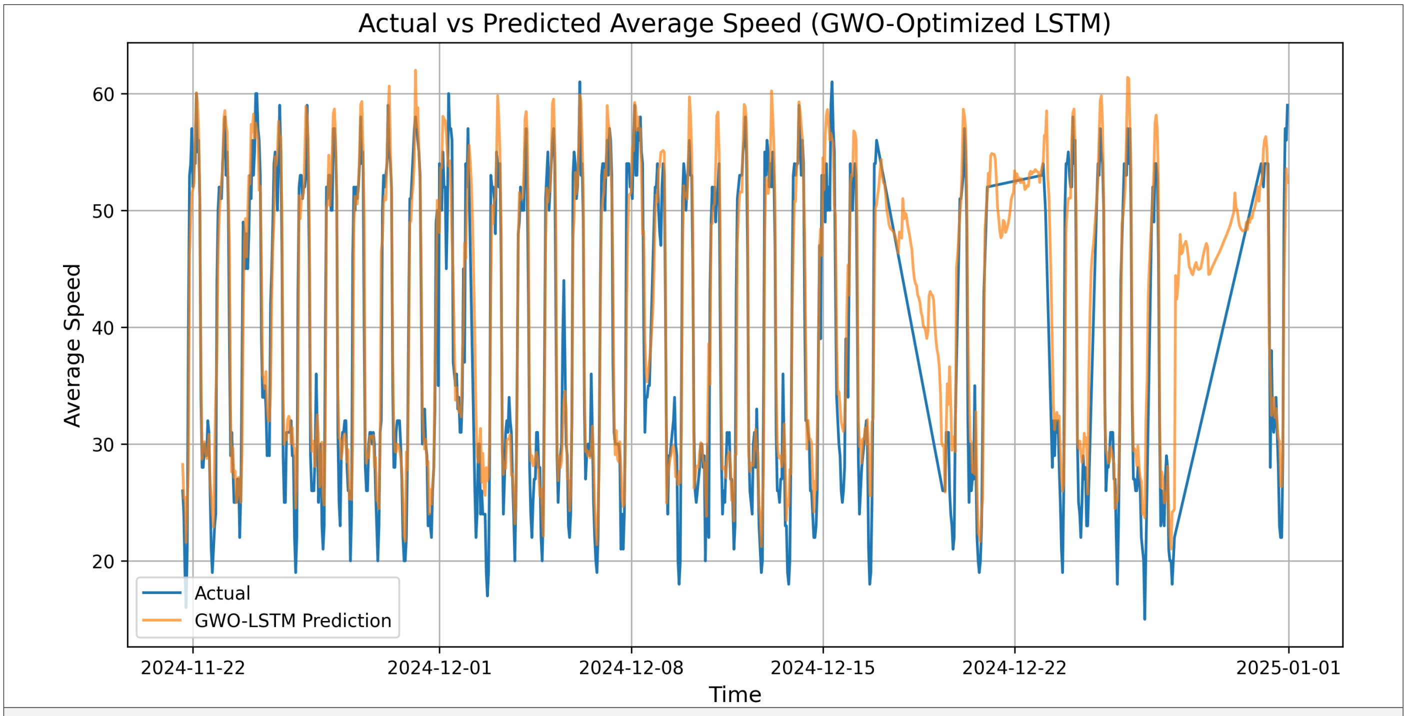

Fig. 8. GWO-LSTM time series prediction performance (actual-predicted average speed).

hyperparameter optimization in complex time series problems such as traffic density prediction.

The computational overhead introduced by GWO was evaluated by measuring the training time and convergence iterations of the baseline and optimized models. On average, the GWO-LSTM model required 18% longer training time compared to standard LSTM, while the GWO-XGBoost model increased computational cost by approximately 12%. Despite this additional overhead, the optimized models converged to significantly better predictive accuracy, with

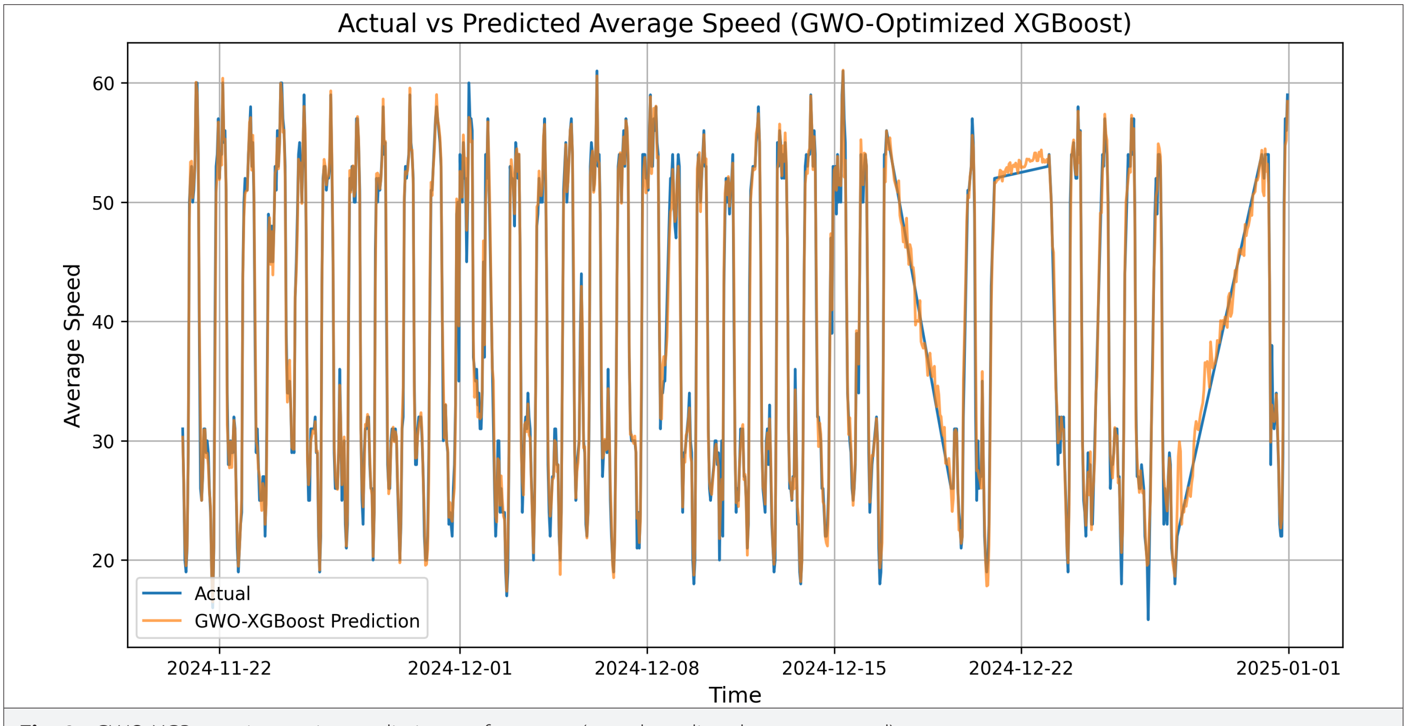

Fig. 9. GWO-XGBoost time series prediction performance (actual-predicted average speed).

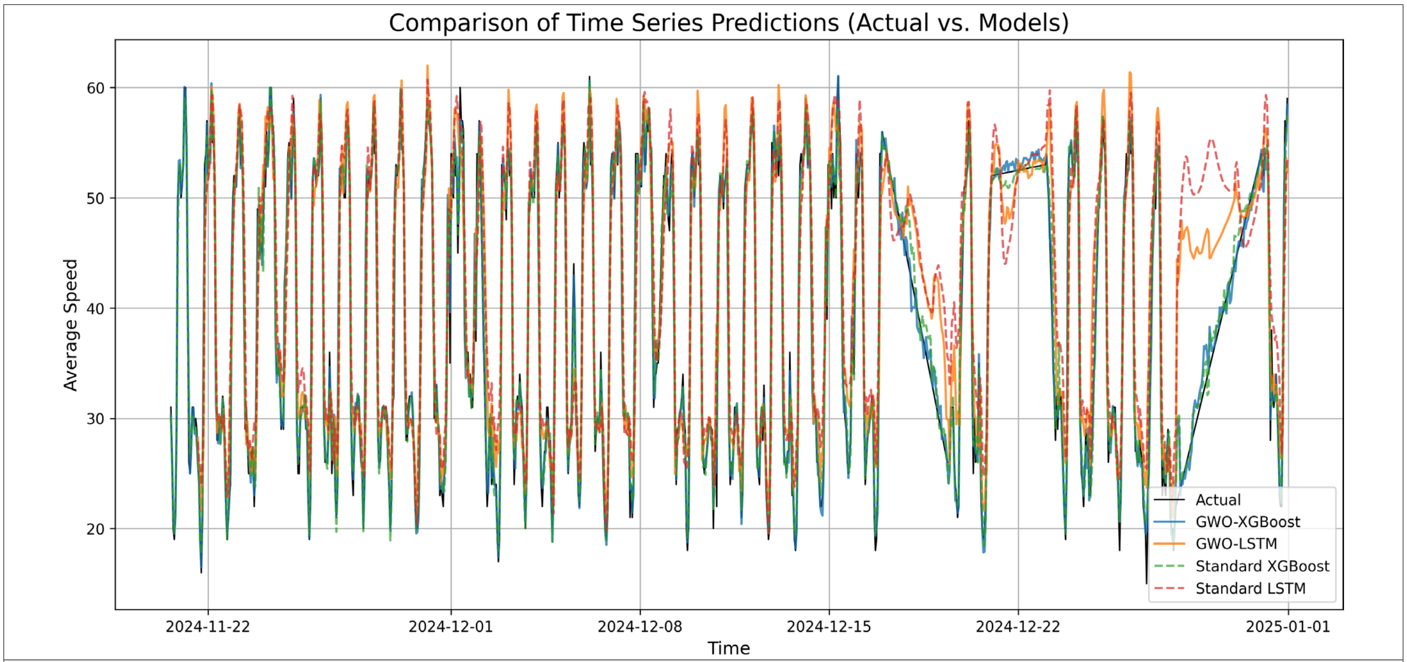

Fig. 10. Comparison of time series predictions (actual vs. models).

reduced error metrics and improved stability across iterations. These results demonstrate that the trade-off between computational efficiency and predictive performance remains favorable, especially in smart city applications where accuracy is critical.

Fig. 12 illustrates a comparative analysis of the R^2 scores obtained by five distinct predictive models: ARIMA, LSTM, XGBoost, GWO-LSTM, and GWO-XGBoost. The R^2 metric, representing the R^2, is used to evaluate the goodness-of-fit for each model. The results demonstrate a significant variance in performance across architecture. The GWO-XGBoost model achieved the highest R^2 score (0.9896), indicating the strongest predictive accuracy and model fit. This was closely followed by the standard XGBoost model, which also showed exceptional performance with an R^2 score of 0.9811. The models incorporating the GWO showed notable enhancements; the GWO-LSTM ($R^2=0.8129$) outperformed its baseline LSTM counterpart ($R^2=0.7341$). The traditional ARIMA model yielded the lowest performance among the group, with an R^2 score of 0.6875.

When the results obtained are evaluated in general, it is determined that both algorithms offer suitable solutions for the traffic speed estimation problem. In the comparison in terms of R^2 value, it was determined that the GWO-XGBoost algorithm showed the highest explanatory power by obtaining the closest value to 1. While the XGBoost algorithm showed consistent performance in both standard and optimized versions, the LSTM algorithm showed significant performance improvements after optimization. In terms of practical applications, model selection for real-time traffic management systems should take into account the factors of computational complexity and processing time as well as prediction accuracy. In light of these findings, it is concluded that the GWO-XGBoost algorithm is the most suitable model for traffic speed forecasting. In this context, the findings of the study provide valuable reference points for traffic engineering applications.

A. Advantages and Limitations

Advantages: High prediction accuracy, robustness to anomalies, flexibility in feature selection.

Limitations: Additional computational overhead, limited performance under extreme traffic fluctuations. Furthermore, the 7-month dataset (June-Dec 2024), while high-resolution, is a limitation as it cannot capture long-term, multi-year seasonal patterns.

V. CONCLUSION

This research has comprehensively evaluated the effectiveness of machine learning approaches supported by the GWO algorithm for

TABLE V. COMPARISON OF MODEL PERFORMANCE METRICS

		MSE	MAE	R^2	WI	PBIAS
Standard	ARIMA	60.1532	5.1204	0.6875	0.7910	±19.4520%
	LSTM	41.2812	4.5585	0.7341	0.8152	±16.6581%
	XGBoost	2.9504	1.1757	0.9811	0.9845	±1.5532%
Hyperparameter optimized	GWO-LSTM	29.0507	3.8432	0.8129	0.8465	±12.1386%
	GWO-XGBoost	1.6209	0.9082	0.9896	0.9874	±0.8486%

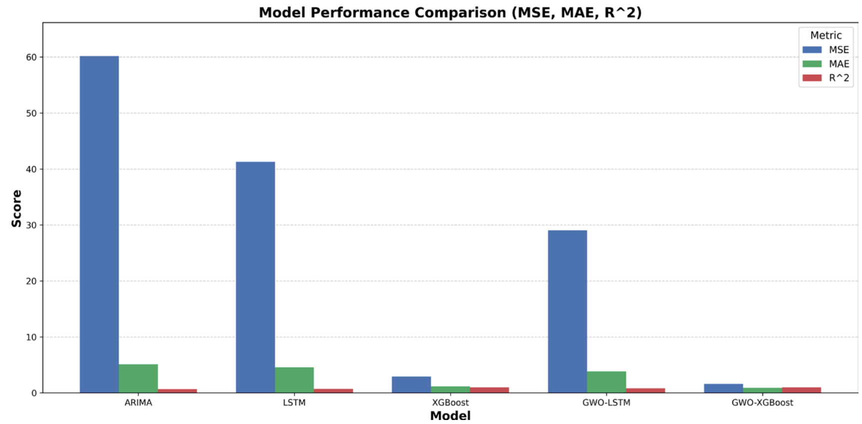

Fig. 11. Model performance comparison (MSE, MAE, R^2).

the analysis of Istanbul's complex urban traffic structure. The findings reveal the critical importance of modern optimization techniques in overcoming the limitations of traditional traffic analysis methods. One of the most important contributions of the study is the systematic comparative analysis of GWO's effectiveness in optimizing different machine learning architectures (LSTM and XGBoost) for traffic data analysis. The developed Unified Traffic Density Index provides a multidimensional evaluation framework by integrating average speed, vehicle density, and speed variation parameters. This approach provided more accurate and reliable traffic density detection compared to traditional single-parameter analysis methods. By integrating GWO into traffic data analysis, the proposed approach demonstrated superior optimization capability and robustness compared to traditional methods, confirming its potential as a reliable tool for intelligent transportation systems.

Algorithmic performance comparisons have shown that GWO optimization significantly improves the predictive capacities of both the LSTM and XGBoost models. In particular, the systematic biases and heteroskedasticity problems observed in the LSTM model are significantly reduced after GWO optimization, and the model's capacity to capture temporal dependencies is improved. The XGBoost algorithm, on the other hand, combines the advantages of the ensemble learning structure with GWO optimization to achieve the highest prediction accuracy and model stability.

According to the findings of time series analysis, strong hourly periodicity structure and weekly fluctuation patterns of Istanbul traffic have been identified. These temporal patterns reflect routine traffic spikes during the morning and evening peak hours but also include random variations due to unexpected traffic events. The GWO-optimized models successfully modeled this multi-layered temporal structure and demonstrated the capacity to adapt to dynamic traffic conditions.

In terms of practical applications, the GWO-XGBoost combination stands out as the most accurate predictive model within this study's framework, suggesting strong potential for use in real-time systems, pending further deployment testing and scalability analysis. The model's high prediction accuracy, low computational complexity, and lack of systematic errors provide critical advantages for operational use in smart city applications. These features provide directly applicable outputs in the development of traffic signalization optimization, route recommendation systems, and proactive traffic management strategies.

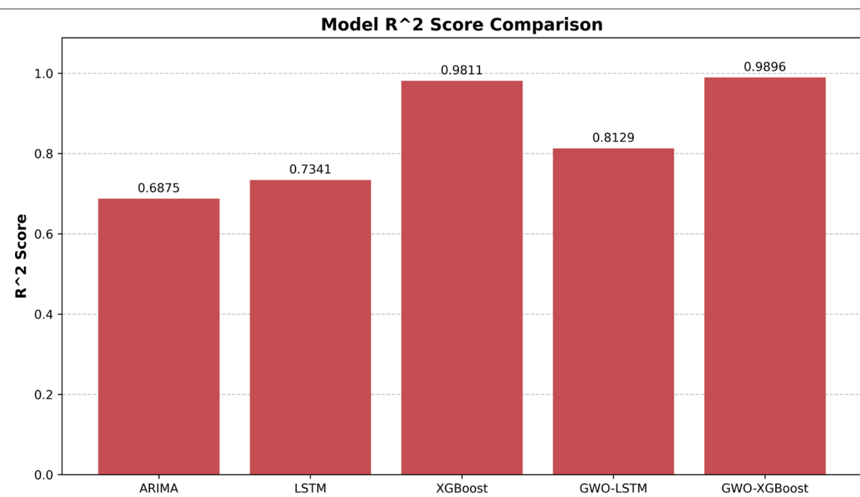

Fig. 12. Model R^2 score comparison.

The methodological contributions of the research include a consensus-based anomaly detection framework and a multi-scale traffic analysis approach. This innovative approach enables consensus-based evaluation of results from different data sources, thereby increasing the level of reliability in anomaly detection. Furthermore, systematic traffic pattern analysis at hourly, daily, weekly, and seasonal scales has provided valuable insights for urban planners and policymakers.

Systematic application of GWO in Istanbul traffic analysis, Unified Density Index, consensus anomaly detection. The GWO-XGBoost outperforms other models with the lowest errors and highest accuracy.

In terms of future research directions, several key areas are considered: the hybridization potential of the GWO algorithm with other meta-heuristic methods, improving its real-time streaming data processing capability, and testing its generalizability to urban traffic systems in different geographical regions. Furthermore, future work must address the limitations of this study by testing the model's scalability and computational viability in a live-streaming environment and evaluating its transferability to other urban districts with different traffic dynamics. Additionally, increasing integration with GIS, IoT sensors, and big data analytics will contribute to the development of more comprehensive urban mobility management solutions.

In conclusion, this study has demonstrated the transformative potential of GWO-assisted machine learning approaches in urban traffic analysis and developed a robust methodological framework that provides actionable intelligence for sustainable urban mobility.

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

Peer-review: Externally peer-reviewed.

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