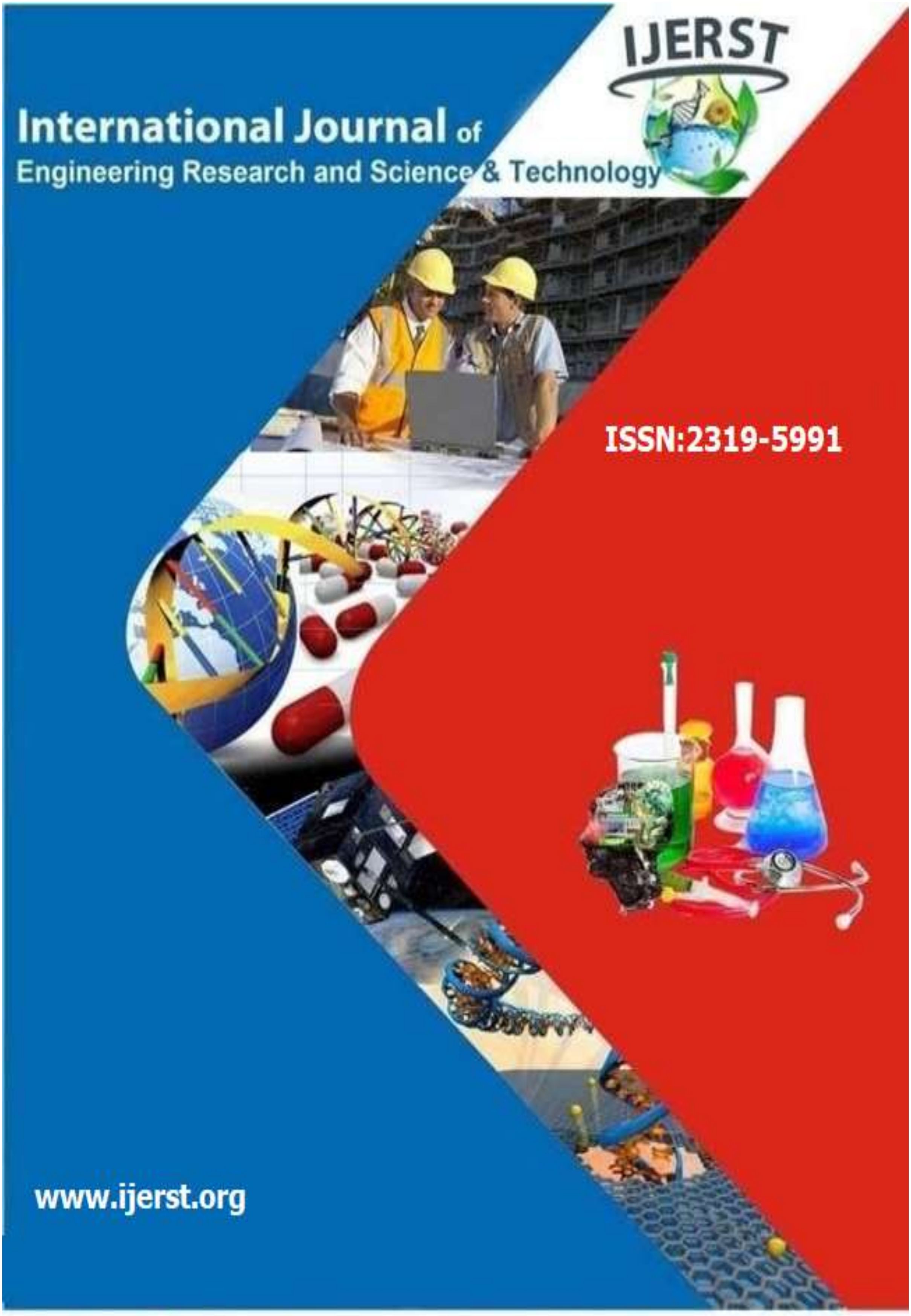

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IOT-BASED TRAFFIC FLOW PREDICTION IN SMART CITY USING EXTREME GRADIENT BOOSTING ALGORITHM

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Abstract

Nowadays, several cities have problems with traffic congestion at certain peak hours, which produces more pollution, noise as well and stress for citizens. The Internet of Things (IoT)-based Intelligent Management System (ITM) is embedded in automatic vehicles and utilized to recognize and transmit data. IoT has been an imminent innovation, moving the globe concerning an automated process as well as (IMS). In this research, the Extreme Gradient Boosting (XGB) is proposed for the prediction of the traffic flow in smart city. XGB is attains the better performance in prediction tasks through the robust handling of complex data structures and relationships. Initially, the data is collected from PeMS07 for estimating the effectiveness of the proposed method. In the pre-processing step, the min-max normalization approach is utilized for the redundancy elimination and minimize data modification errors in the collected dataset. The ResNet101 architecture is utilized to extracting the features from the pre-processed data. The proposed XGB approach attains the MAE of 22.56%, MAPE of 10.46% and RMSE of 35.46% respectively when compared to the existing methods such as DDGCRN.

Keywords: Intelligent Management System, Internet of Things, ResNet101, Traffic Prediction and Extreme Gradient Boosting.

1 Introduction

Controlling traffic signals in urban areas is a significant process and it is an essential topic in recent developments [1]. Today, a number of cities have issues with traffic congestion at peak hours, which generates pollution, noise as well and stress for citizens [2]. The city officials have expanded public transportation to reduce traffic congestion. Moreover, it plans to extend metro lines to decrease traffic congestion and minimize safety levels in the city. [3]. Accidents, bad weather, slow-moving overloaded vehicles, vehicle breakdowns, physical road conditions, and so on are some of the components that contribute to the issues of congestion [4]. The most significant and basic element of solving these traffic problems is the precise estimation of the recent situation of road traffic jams [5]. The manual traffic systems in smart cities require greater manpower and those approaches have seriously poor traffic schemes and consume much time for the prediction. With the aim of resolving the problem, the traffic signal systems are ingrained in metropolitan areas. Thus, the frequency parts of traffic lights are identical as well as resolute for all the roads [6][7].

An Intelligent Transport Management (ITM) system is majorly utilized to address the traffic congestion problems [8]. The ITM systems can minimize traffic congestion and improve transportation quality for organizations. The intelligence and dependability of IoT-based ITM Systems development depend on solutions executed to enhance individual standards of living [9][10]. IoT involves linking physical things to the internet to design intelligent networks as well

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as mobile communication connectivity with contemporary materials like ITM. IoT is a constitution of data acquisition and determination of sensor data as well as estimation to effectively control and support the traffic networks [11][12]. The existing research utilized the Machine Learning (ML) and Deep Learning (DL) approaches to solve the complicated traffic issues [13][14]. Thus, there is a likelihood that the data involved in a specialist knowledge base for traffic accidents is not correct. Many research works residues to analyse how to accurately extract traffic accidents from traffic data flow [15]. In this research, an IoT-based traffic flow prediction is proposed by using Extreme Gradient Boosting (XGB) approach. The major contributions of this research are as follows:

- The Min-max normalization technique is used for pre-processing the data from the collected dataset. The Min-max normalization ensures that all features contribute equally, reducing bias towards features with inherently larger values and it leads to enhanced model performance.
- The Convolutional Neural Network (CNN) architecture of the ResNet-101 is utilized for extracting the relevant features. The ResNet-101 enables the extraction of high-level representations and it capture intricate patterns in traffic flow data, leads to enhance the better accuracy results.
- The XGB approach is proposed for the prediction of traffic flow in smart cities. The XGB allows the model to process large volumes of traffic data quickly and it leads to better performance.

The rest of the paper is organized as follows: Section 2 describes the Literature review. The proposed model is presented in Section 3. Results and discussion are illustrated in Section 4. The conclusion is described in Section 5.

2 Literature Survey

In this section, the existing works related to prediction of traffic flow using PeMS07 dataset is discussed along with their advantages and limitations.

Jin Fan *et al.* [16] implemented a Decomposition Dynamic Graph Convolutional Recurrent Network (DDGCRN) for the prediction of traffic flow within road networks. DDGCRN was integrated with Recurrent Neural Network (RNN) to create a dynamic graph built on time-varying traffic signals, which empowers the extraction of both spatial and temporal features. The DDGCRN performance was better because it has the capability to capture both spatial and temporal dependencies efficiently. However, the predefined graph structure greatly affects model output because spatial relationships through static graph structures lead to low prediction rates or inaccuracy.

Xiaoyong Sun *et al*. [17] introduced the traffic prediction models for large-scale traffic networks using Spatial-Temporal Shared Gated Recurrent Unit (STSGRU). STSGRU received input from various sensors and provided predictions from all sensors concurrently. The existing model from different shared weight mechanisms to achieve various predictions without mapping traffic networks to images. The model accomplishes prediction with advanced graph neural networks which have more flexibility. However, the model scalability was poor and not able to provide accurate predictions for large-scale traffic predictions, because in real-time processing prediction of large-scale traffic systems was challenging.

Ya Shen *et al.* [18] implemented an adoptive Graph Convolution Recurrent Network (GCRN) and Whale Optimization Algorithm (WOA) for traffic flow prediction. The implemented network automatically deduced the correlation among different traffic sequences and included the capability to capture global spatiotemporal correlations which enables long-range temporal

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correlations. This design approach significantly maximizes the model performance and improves the accuracy of traffic flow prediction. However, the design of network architecture was crucial for achieving optimal performance because it was difficult to represent the patterns and relationships between the data.

Wei Lu *et al*. [19] presented Adaptive Spatial-Temporal Graph Attention networks (ASTGAT) for traffic flow control. ASTGAT learns the dynamic graph structure and spatial-temporal dependency for traffic flow forecasting. The framework includes two joint training parts: a network generator model that generated a discrete graph with the Gumbel-softmax technique and a spatial-temporal model that utilized the generated network to identify traffic speed. However, the GTHA only focused on spatial-temporal dependence through a fixed-weighted graph based on prior knowledge, because uncertainty occurs in road networks and traffic conditions, leading to poor model performance.

Dongfang Yang *et al*. [20] implemented a graph Deep Learning (DL)-based rapid traffic flow prediction in urban road networks. The Graph Convolution Network (GCN) was used to recognize a novel forecasting technique for graph-level traffic flow. The convolution operations minimize computational complexity in the convolution process because the convolution operations in the time domain were transferred into multiplication operations in the spectral domain. However, the method does not perform feature extraction because it contains more fine-grained features when modelling traffic networks leading to insignificant performance of the model.

From this section, some of the limitations have been identified such as affecting the output of model structure due to spatial relationships, poor model scalability was poor, incapable to provide accurate predictions for large-scale traffic predictions, difficult to represent the patterns and relationships between the data as well as lack of performing the feature extraction process. Hence, to solve these problems, this research proposes the XGB approach for the prediction of traffic flow in smart cities.

3 Proposed Methodology

This research proposes the XGB approach for the prediction of traffic flow in smart cities. This research comprises two important steps such as data collection, pre-processing, feature extraction and prediction. Figure 1 depicts the workflow of the proposed method.

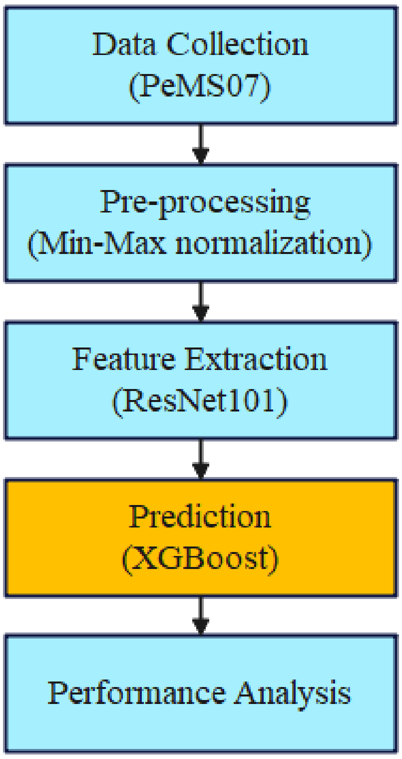

Figure 1. Workflow of the proposed method

3.1 Data Collection

In this section, training and evaluating the proposed model on real-world dataset collected by Caltrans Performance Measurement System (PeMS), which is the most commonly utilized dataset in traffic flow prediction. The data is collected at the frequency of each 30 seconds and it is collected on the California highways. The collection of the data is aggregated into 5 minutes windows, which is considered as the time steps and every hour involves 12-time steps. The PeMS07 [21] data involves the 883 nodes with 866 edges and the time steps of 28224 respectively. The aim of this research is to use the historical data from an hour to the prediction of next hour. Then, the collected dataset is then provided to the pre-processing step.

3.2 Pre-processing

The data preprocessing is performed before feature extraction because it contains the missing values, so it leads to poor performance. Identifying missing values in datasets is a significant task for enhancing the model performance. The missing values identification is a process of converting raw data into a suitable format, the dataset from various resources may contain incomplete data. It is used to improve the efficiency, accuracy, and data quality for developing meaningful perception extraction through the data. For further analysis, the data is to be normalized because the collected dataset involves various sizes and units, so it leads to poor accuracy results. Hence, the min-max normalization [22] is the process of equally scaling the input values in the range between 0 and 1 and there is no change in the distribution of data. The min-max normalization is expressed in equation (1) as;

$$X = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Where, X - normalized attribute; x_{max} – attribute maximum value; x_{min} – attribute minimum value; and x_i – actual data. Then, the normalized features are provided to the feature extraction process.

3.3 Feature Extraction

The feature extraction is performed after image preprocessing. The feature extraction method is an effective tool to

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extract the important informative features for the reduction of dimension. It is used to reduce the number of required sources to describe a large amount of data. A large number of image-strength grades are provided for feature extraction. An output of high-level data such as shape, colour, texture etc. The features are extracted by utilizing an architecture of the Convolutional Neural Network (CNN) [23]. Hence in this research, the ResNet-101 is utilized for the extraction of the relevant features. The detailed description of the ResNet-101 is provided below.

3.3.1 ResNet-101

As compared to other pre-trained model, the ResNet-101 captures complex and abstract features and it allows for better representation of intricate patterns in traffic data. Thus, ResNet101 architecture is the pre-trained CNN model utilized for the feature extraction. The Residual Network is abbreviated as the ResNet and it is one of the architectures of Convolutional Neural Networks, majorly utilized to extract image features [24]. Figure 2 depicts the ResNet-101 architecture.

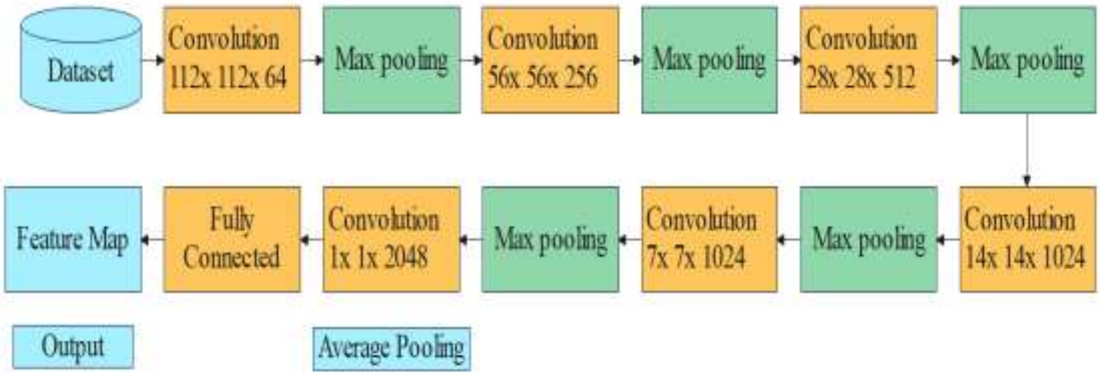

Figure 2. ResNet101 Architecture

This model produced the default size of the feature map of $10 \times 10 \times 2048$ in the final convolutional layer. If feature vector size is similar, and easy to integrate vectors extracted using ResNet101 in a single feature vector. In ResNet101, a modification is employed in spreading association descriptions among the blocks. Considering the size of the input as $[300 \times 300]$ and its creation employing basic convolution and max-pooling used $[7 \times 7]$ and $[3 \times 3]$ kernel sizes separately. ResNet101 consists of multiple residual blocks each with three layers. In each three-square level, a kernel used to act is 64 or 128 bits in size. The size of the input is minimized compared to height and width, but channel width gets twice multiple layers are located on each residual function's top and convolutions are utilized in $[1 \times 1]$ and $[3 \times 3]$ layers. The $[1 \times 1]$ layers are dependable to minimize then dimensions restore. The $[3 \times 3]$ the layer is blockage using the lesser input/output dimensions. At last, it has an average pooling layer and is followed by a fully associated layer using 2048 feature. Then, the extracted features are provided to the prediction of the traffic flow.

3.4 Traffic Flow Prediction

The extracted features are provided as input to the prediction of traffic flows. In this process, the ML-based prediction approach uses a number of layers to collect complicated patterns and relationships within the data. In this research, the XGB approach is utilized for the prediction of traffic flows, and a detailed information on this approach is provided in below.

3.4.1 Extreme Gradient Boosting

The XGB is Machine Learning (ML) approach based on the boosting trees, which has the capability to capture the complex nonlinear relationships among the group of

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predictors as well as output variables. The XGB is majorly works for the problem of classification and regression trees based on the approach similar to the Gradient Boosting Machine (GBM) with particular model structural variations. The XGB performs the second-order derivatives, while the traditional GBM uses the first-order derivatives. As compared to GBM, the XGB is the most efficient as well as less likely to result in the approach overfit as it utilizes the enhanced regularized functions. The parallel processing in XGB speed ups the GBM approaches as well as provides better effectiveness than the GBM.

Basically, the regression problems involving the input variables $\left(x_i \in R^d \, where \, i = 1,2, \dots n\right)$ and n is the number of input variables. The target variable $(x_i \in R)$ is performed for the classification and regression tree process, the ensemble approach utilizes the basic form of classification and regression tree is formulated in equation (2) as follows:

$$\hat{y}_i = \varphi(x_i) = \sum_{k=1}^{K} P_k(x_i), t_k \in \mathcal{F} \quad (2)$$

Where, $\varphi(x_i)$ denotes the function which represents the model input to the model prediction $(\hat{y}_i \in R)$ where, $\mathcal{F} = \{p(x) = w_{q(x)}\}(q: R^m \to T, w \in R^T)$ denotes the entire space of the regression tree; P_k denotes to the single tree structure, the number of leaves in the tree P_k is T as well as leaf weights are w. The aim of XGB involves the loss function as well as regularization term is formulated in equation (3) and (4) as follows:

$$\mathcal{L}(\emptyset) = \sum_i I(\hat{y}_i, y_i) + \sum_k \Omega(P_k) \quad (3)$$

$$\Omega(p) = \gamma T + \frac{1}{2}\lambda \|w\|^2 \quad (4)$$

Where, I denotes the differentiable convex loss function which is utilized for estimating the variance of target (y_i) and prediction $(\hat{y}_i)$ during training the period; Ω represents the regularization term, which penalizes an objective function based on the model complexity.

Since the traditional approaches of the model optimization are inappropriate for the tree ensemble approach (XGBT). In this approach, the function (p_t) is extended to enhancing the model for the prediction of $\left(\hat{y}_i^{(t)}\right)$ at ith instance after ith iteration is formulated in equation (5) as follows:

$$\mathcal{L}^{(t)} = \sum_{i=1}^{n} I\left(y_i, y_i^{(t-1)} + P_t(x_i)\right) + \Omega(P_t) \quad (5)$$

The second-order expansion of Taylor series is utilized for rapidly optimizing the objective functions through equation (6) as follows:

$$\mathcal{L}^{(t)} \simeq \sum_{i=1}^{N} \left[I\left(y_i, y_i^{(t-1)}\right) + g_i P_t(x_i) + \frac{1}{2} h_i P_t^2(x_i)\right] + \Omega(P_t) \quad (6)$$

The gradient statistics of the loss function for the first order g_i as well as seconder order h_i are formulated in equations (7) and (8) as follows:

$$g_i = \partial_{\hat{y}^{(t-1)}}\left(y_i, y_i^{(t-1)}\right) \quad (7)$$

$$h_i = \partial_{\hat{y}^{(t-1)}}\left(i, y_i^{(t-1)}\right) \quad (8)$$

Through eliminating the constant term for step t, an objective function is minimized, which is formulated in equation (9) as follows:

$$\mathcal{L}^{(t)} = \sum_{i=1}^{N} \left[g_i P_t(x_i) + \frac{1}{2} h_i P_t^2(x_i)\right] + \Omega(P_t) \quad (9)$$

Through describing $I_j = \{i | q(x_i) = j\}$ as well as Ω is enhanced through equation (10) as follows:

$$\tilde{\mathcal{L}}^{(t)} = \sum_{i=1}^{N} \left[g_i P_t(x_i) + \frac{1}{2} h_i P_t^2(x_i)\right] + \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2 = \sum_{j=1}^{T} \left[\left(\sum_{i \in I_j} g_i\right) w_j + \frac{1}{2}\left(\sum_{i \in I_j} h_i + \lambda\right) w_j^2\right] + \gamma T \quad (11)$$

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For the fixed structure of $q(x)$, the weight $\left(w_j^*\right)$ as well as consequent optimal value $\left\{\left(\tilde{\mathcal{L}}^{(t)}\right)(q)\right\}$ of leaf (j) is formulated in equation (12) and (13) as follows:

$$w_j^* = -\frac{\sum_{i\in I_j} g_i}{\sum_{i\in I_j} h_i+\lambda} \tag{12}$$

$$\tilde{\mathcal{L}}^{(t)}(q) = -\frac{1}{2}\sum_{j=1}^{T}\frac{\left(\sum_{i\in I_j} g_i\right)^2}{\left(\sum_{i\in I_j} h_i+\lambda\right)} + \gamma T \tag{13}$$

The solution for this problem is acquired by the approach which extends the branches to the tree from the ingle leaf at every iteration.

4 Experimental Results

The proposed XGB approach is implemented on Python 3.10 with the system configuration of windows 10 OS, intel i5 processor and 8GB RAM respectively. the proposed method is evaluated by using various performance metrics. The performance metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are utilized to validate the performance of the model. The performance was estimated by utilizing the traffic prediction IoT dataset. The mathematical representation of the performance metrics is as formulated in the equations (14) to (16) as follows:

$$MAE = \sqrt{\frac{1}{m}\sum_{i=1}^{n}|y_i - \hat{y}_i|} \tag{14}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i) \tag{15}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{16}$$

Where, n - number of points; y_i - predicted value obtained from the neural network; $\hat{y}_i$ - the real value.

4.1 Performance Analysis

This section shows quantitative analysis and qualitative analysis of the proposed method compared with existing methods in terms of achievable sum rate. The ResNet101 and XGB method is evaluated using various performance metrices based on the PeMS07 dataset. Table 1 and 2 depicts the performance analysis of the feature extraction and classification results.

Table 1. Performance analysis of the feature extraction results

Methods	**MAE (%)**	**MAPE (%)**	**RMSE (%)**
Inception Net	17.33	6.13	30.17
VGG-16	18.39	7.12	31.34
AlexNet	19.93	7.39	32.93
ResNet-50	20.39	8.39	33.39
ResNet-101	22.56	10.46	35.46

Table 1 shows the introduced ResNet-101 architecture with various feature extraction approaches based on the PeMS07 dataset. The existing feature extraction approaches like Inception Net, VGG-16, AlexNet and ResNet-50 are considered for the estimation purpose. As compared to these existing approaches, the proposed ResNet-101 often attains higher accuracy in prediction tasks because of its deeper architecture and more sophisticated design. This results in better feature extraction and representation, which is significance for capturing complex patterns in traffic flow data. The proposed ResNet-101 attains the MAE of 22.56%, MAPE of 10.46% and RMSE of 35.46% respectively.

Table 2. Performance analysis of the feature extraction results

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Methods	MAE (%)	MAPE (%)	RMSE (%)
DT	18.47	7.92	32.86
RF	19.45	8.78	33.98
AdaBoost	20.38	9.12	34.02
CatBoost	21.39	9.82	34.29
XGB	22.56	10.46	35.46

Table 1 shows the introduced XGB approach with various classification approaches based on the PeMS07 dataset. The existing classification approaches like Decision Tree (DT), Random Forest (RF), CatBoost and AdaBoost are considered for the estimation purpose. As compared to these existing approaches, XGB provides insights into feature importance, helping to identify the factors which most significantly affect traffic flow, guides the infrastructure enhancement and decision-making. The proposed XGB approach attains the MAE of 22.56%, MAPE of 10.46% and RMSE of 35.46% respectively.

4.2 Comparative Analysis

In this section, the effectiveness of the proposed XGB approach is compared with the previous approaches based on the PeMS07 dataset. The existing methods like DDGCRN [16], STSGRU [17] and WOA-AGCRTN [20] are compared with the proposed XGB approach by using various performance metrices. Table 3 depicts the comparative analysis using PeMS07 dataset.

Table 3. Comparison Results

Methods	MAE (%)	MAPE (%)	RMSE (%)
DDGCRN [16]	2.59	6.48	5.21
STSGRU [17]	21.50	9.08	34.40
WOA-AGCRTN [18]	20.57	8.74	34.06
Proposed XGB	22.56	10.46	35.46

4.3 Discussion

In this section, the achievement of the proposed XGB approach is discussed along with its advantages. The existing works have limitations such as the predefined graph structure in DDGCRN [16] greatly affects model output because spatial relationships through static graph structures lead to low prediction rates or inaccuracy. In STSGRU [17], the model scalability was poor and not able to provide accurate predictions for large-scale traffic predictions, because in real-time processing prediction of large-scale traffic systems was challenging. The GCRN-WOA [18] was difficult to represent the patterns and relationships between the data. The ASTGAT [19] had only focused on spatial-temporal dependence through a fixed-weighted graph based on prior knowledge, because uncertainty occurs in road networks and traffic conditions, leading to poor model performance. GCN [20] does not perform feature extraction because it contains more fine-grained features when modelling traffic networks leading to insignificant performance of the model. Hence, this research proposes the XGB approach for the prediction of traffic flow in smart cities. XGB provides insights into feature importance, helping to identify the factors which most significantly affect traffic flow, guides the infrastructure enhancement and decision-making.

5 Conclusion

In this research, the prediction of traffic signals in smart cities by proposing the Machine Learning (ML) approach of XGB. The XGB allows the model to process large volumes of traffic data quickly and it leads to better performance. The min-max normalization method is utilized for the

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enhancement of the dataset and the CNN architecture of ResNet101 is utilized for the extraction of the feature. the proposed ResNet-101 often attains higher accuracy in prediction tasks because of its deeper architecture and more sophisticated design. This results in better feature extraction and representation, which is significance for capturing complex patterns in traffic flow data. The proposed XGB approach attains the MAE of 22.56%, MAPE of 10.46% and RMSE of 35.46% respectively when compared to the existing methods such as DDGCRN and STSGRU. In the future, this proposed method will extend to solve the data imbalance issues to improve the accuracy of results.

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