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Urban Travel Demand Modelling for Indian condition Using IoT-based Traffic Prediction

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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 IoT-based Intelligent Management System (ITM) is embedded in automatic vehicles and utilized to recognize and transmit data. The IoT has been an imminent innovation, moving the globe concerning an automated process as well as (IMS). In this paper, the Internet of Things (IoT) based traffic signal prediction is proposed using the Attention based VGG-16. The proposed Attention based VGG-16 is evaluated on the road traffic IoT dataset which contains information about the traffic, number of vehicles, and road information. 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 of Convolutional Neural Network (CNN) is utilized to perform image classification of traffic. The proposed method achieves the better results by utilizing evaluating metrices like accuracy, precision, recall and Mean Absolute Error values about 99.36%, 99.25%, 98.57% and 0.72 respectively which is comparatively higher than existing techniques like Optimized Weight Elman Neural Network (OWENN), CNN and Capsule Neural Network.

Keywords
VGG-16, Neural Network, Intelligent Management, Internet of Things, ResNet101, Traffic Prediction.

1. Introduction
Controlling traffic signals in urban areas is a significant process and it is an essential topic in recent developments stated by Lee, W.H. and Chiu, C.Y., 2020. Today, a number of cities have issues with traffic congestion at peak hours, which generates pollution, noise as well and stress for citizens given by Arifin, A.S. and Zulkifli, F.Y., 2021. 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. Fadda et al 2022. 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 marked by Giusto, D.D. et al. 2022. The most significant and basic element of solving these traffic problems is the precise estimation of the recent situation of road traffic jams mentioned by Ahmad, M et al. 2022. The manual traffic systems in urban 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 stated by Jafari, S. et al. 2022 and also by Ramesh, K., 2021.

An Intelligent Transport Management (ITM) system is majorly utilized to address the traffic congestion problems (Jafari, S., 2022). 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 (Omar, A et al. 2022) and by (Dhingra, S. el al. 2021). IoT involves linking physical things to the internet to design intelligent networks as well 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 mentioned by (Navarro-Espinoza,et al 2022) and (Lilhore, U.K., et al. 2022). The existing research utilized the Machine Learning (ML) and Deep Learning (DL) approaches to solve the complicated traffic issues stated by Tian, Y., 2022 and Lohrasbinasab, I. et al 2022. 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 analyze how to accurately extract traffic accidents from traffic data flow mentioned by Li, P., Zhang, Y.,in 2021. In this research, an IoT-based traffic signal prediction is proposed using the Attention-based VGG-16. The major contributions of this research are as follows:

- The min-max normalization method is used for image pre-processing for redundancy elimination and to minimize data modification errors in the collected dataset. The ResNet101 architecture of the CNN is used for extracting the relevant features of the traffic data.
- An Attention-based VGG-16 classification algorithm using IoT is proposed for predicting the traffic signal in the urban city. The proposed method is evaluated by using evaluation metrics like accuracy, precision, recall, and MAE.
- 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

S. Neelakandan *et al*. 2021 developed an IoT-based traffic prediction based on the Optimized Weight Elman Neural Network (OWENN) classification approach for the urban city of traffic signal control. The OWENN algorithm could effectively predict the traffic to increase the performance with the intel 80286 microprocessor under the management of traffic. This OWENN was utilized to classify where the place had more traffic. This method achieved better accuracy and classification results. However, this method required a longer time period to train the model as well as storage issues.

Umair Jilani *et al*. implemented a multiple-layered Convolutional Neural Network (CNN) of deep learning for the classification of traffic congestion. This method can be utilized for local traffic planning as well as maintenance managers and stakeholders for the effective development of Intelligent Transportation Systems (ITS). This method has achieved better accuracy results compared with ResNet50 as well as denseNet-121. However, this method did not classify the all images as well as required a longer period to train the model.

Chuanxi Niu and Kexin Li in 2022 implemented detection and classification with the YOLOV5 and AlexNet for traffic light detection. The YOLOV5 was used to detect and extract the traffic light area, and AlexNext pre-trained model was utilized the classify the traffic data. This method utilized the ZeroDCE low-light improvement algorithm to optimize the dataset, and after the optimization of the dataset, the trained network performance was enhanced. This method achieved better performance results due to the combination of YOLOV5 and AlexNet. However, the YOLOV5 does not detect the small images within the group of images.

Xiaoxu Liu and Wei Qi Yan in 2021 developed a deep learning method of Capsule Neural Network (CapsNet) for traffic light sign recognition with automated vehicles. The CapsNet approach was utilized to efficiently recognize the traffic light signs. This method solves the problems of misunderstanding by utilizing CNN in the recognition as well as max-pooling loss. This method achieved high robustness in image recognition, but the method has only been tested on large image datasets.

Hong Chen *et al*. 2021 implemented a Naïve Bayes classification algorithm for the recognition of traffic light signals. This method enhanced the algorithm by utilizing the feature weighting as well as Laplace calibration and the enhanced algorithm. This method utilized the greater likelihood evaluation principle to classify the sample into the most liked category. This method achieved better accuracy by utilizing fewer sample amounts to train the model and it required only a small number of performance metrics. However, this method is unable to examine the feature interactions, size of the sample, and category.

The above section provides some limitations such as consuming a longer period to train the model, storage issues, lack of spatial information, unable to examine the feature interactions, sample sizes, and categories. To overcome this, IoT-based traffic signal prediction in the urban city using the Attention-based VGG-16 is proposed to solve these problems.

3. Proposed Methodology

The proposed CNN algorithm is utilized for the traffic signal control system in a urban city. This section consists of five different processes which include collection of data, image pre-processing, feature extraction, classification, and finally traffic signal control system. Figure 1 represents the block diagram of the proposed methodology.

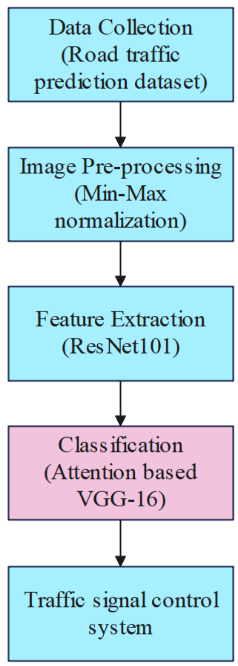

Figure 1. Block diagram of the traffic signal prediction

3.1 Data Collection

The first stage of the proposed method is a collection of data, which is collected from a public repository of road traffic prediction IoT datasets. This dataset is derived from the sensors and cameras, and the information is collected from the traffic environment. This dataset contains information about traffic information, vehicle information as well as road information. This information can be utilized to predict the traffic designs as well as adjust the stop-light control parameters. It consists of recorded data from 6 crosses in city areas for approximately two months, in length form of a time series, representing more vehicles passing 5 minutes for an entire data, which is endorsed for short-term predictions. The dataset is split into two parts such as 75% (45 days) of data utilized for training and 25% (15 days) for testing. After the dataset collection in the traffic signal, the data proceeded to the image pre-processing.

3.2 Image Preprocessing using Min-max Normalization

The image preprocessing is performed before feature extraction because it contains the missing values and data. The data pre-processing is a needed task for identifying missing values in datasets denoted by zeros because of failures of sensors. It is a process of converting raw data into a suitable format, the dataset from various resources may contain incomplete data. The model was 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 due to processing the missing values in the dataset. The min-max normalization (Zhao, R., et al, 2021) is the process of pre-processing input data which is scaled between 0 and 1 and there is no change in the distribution of data. The min-max normalization is done before the extraction of the feature and it 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;

The normalization of intensity scales the values of intensity between $[0,1]$ and resized data to 227×227 before feeding into the feature extraction.

3.3 Feature Extraction using ResNet101

The feature extraction is performed after image preprocessing. The feature extraction method is an effective tool to 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, color, texture etc. The features are extracted by utilizing a Convolutional Neural Network (CNN) (Bharadiya, J.P., 2023). The CNN involved two kinds of such as fully connected layers to accomplish classification as well as the convolutional layers to extract the image features of lower and higher order. These are the most commonly utilized architectures in the CNN model to achieve prominent achievement, especially in detection. Thus, ResNet101 architecture is the pre-trained CNN model utilized for the feature extraction. 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. The Residual Network is called the ResNet. The ResNet is one of the architectures of Convolutional Neural Networks, that is utilized to extract image features, convolutional layer with 101 deep layers is called the ResNet101 implemented by Rafiq et al, 2022. 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 blockaged 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. Figure 2 shows the basic ResNet101 architecture.

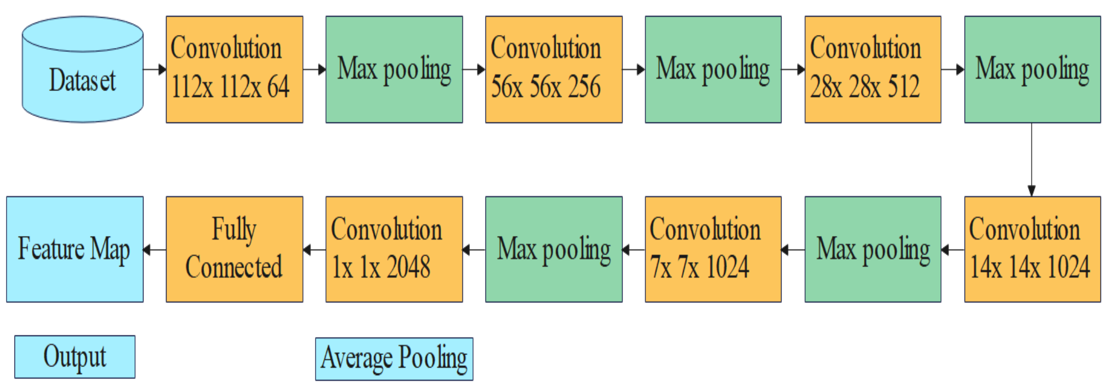

Figure 2. ResNet101 Architecture

3.4 Classification using Attention-based VGG-16

The output of the extracted features is given as input to image classification. In this section, the attention-based VGG-16 is utilized for the classification. The VGG-16 (Muhtasim, D.A et al 2022) is the famous CNN version known as VGG-16. The VGG-16 contains 16 layers such as 13 convolutional and 3 fully connected (FC) layers and which is shown in Figure 3. It carries the input as $[224 \times 224]$ pixels color image size and classify it into the 1000 classes mention by AATILA et al, 2021. Hence, it provides the size vector 1000, which consists of the probabilities of belonging to each class. Each convolutional layer utilizes the color filters of $[3 \times 3]$ pixels passes using the step of 1 pixel. The number of filters differs on the block in which the layer is placed. Each convolutional layer activates a ReLU function as well and the ReLU correction layer is placed after the convolution layer. The operation of pooling is accomplished using the size of cells $[2 \times\times 2]$ pixels and a step of 2 pixels, thus the cells do not overlap. The first two fully connected layers estimate a size vector 4096 followed by the ReLU layer.

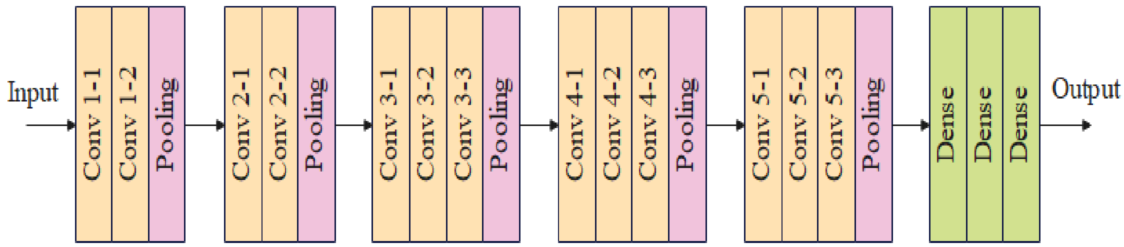

Figure 3. VGG-16 architecture

The attention-based VGG-16 contains a number of building blocks and it can be discussed below.
Attention Module
The attention module was utilized to catch the spatial relationship of optical identification in the traffic signal control system. The max pooling as well as average pooling on the input matrix was performed, which is the fourth pooling layer of this method. Then, the multiple resultants' matrix is integrated to employ a convolution filter size of $[7 \times 7]$ utilizing the sigmoid function (σ). The integrated resultant matrix ($M_s(F)$) is expressed in equation (2) as;

$$M_s(F) = \sigma\left(f^{7\times7}\left[F^s_{avg}; F^s_{max}\right]\right) \quad (2)$$

Where, $F^s_{avg} \epsilon R^{1\times H\times W}$ and $F^s_{max} \epsilon R^{1\times H\times W}$ - 2D matrix attained with average and max-pooling operation on the input matrix F. H and W – matrix's height and width.

Convolution Module
The convolution module is fourth pooling layer of this model. The fascinating hints are extracted from the middle layer, and it is suitable for images. However, features from the various layers are not suitable to the images due to that images have basic or significant. Hence, the input of the fourth pooling layer to the attention module after that module result is integrated with the pooling layer individually.

Fully Connected layers
An integrated feature attained from a block of attention as well as convolution into one-dimensional features, in this method utilized the FC layers. It contains multiple layers such as flatten, dropout as well as dense and set dropout for 0.5 and dense layer for 256.

Softmax Classifier
The features extracted from FC layers are utilized for softmax. Softmax layer is last dense layer and its unit number depends on the various categories. It outputs a multimodal distribution of probability scores using the classification employed and the output of distribution is expressed in equation (3) as

$$P(a = c|b) = \frac{e^{b_k}}{\sum_j e^{b_j}} \quad (3)$$

Where, b and c – probabilities recovered from the softmax layer. It can accurately recognize which places have more traffic and the classified image output is given as input to the traffic control system.

3.5 Traffic signal control system

The traffic signals are monitored with an Intel 80286 microprocessor in the phase. It gives significant operations to permit the effective operating system deployment as well as execution. It supports virtual memory architecture by contributing deviation and restartable direction to non-current segments. The microprocessor contains four-unit blocks and the working principle of these blocks is individually discussed below.

Address unit: It is the initial process and it is evaluated for physical address in obtained data or directions. The obtained address is proceeded to the bus unit after analysis of physical addresses.
Bus unit: It is gathered from memory using a data bus and it can obtain directions earlier from memory, then restore the units in the queue from smoother directions execution and after providing it instruction unit.
Instruction unit: It decodes instructions when directions are extracted from the queue, The decoder often pays attention to directions as well as stores them into a suitable decoded list, and it can fix the vehicle's waiting time using the IoT values
Execution unit: The decoded instruction queue is used for the execution unit. It enhances the waiting time, where a place has more traffic with IoT values and supplies easy and safer moves of the vehicles in traffic.

The 80286 microprocessors automatically monitor traffic signals using the IoT values. It gives significant operations to permit the effective operating system deployment as well as execution. It supports multitasking because multiple programs can be executed using virtual memory, and which is low power consumption, high power, and more reliable.

4. Results and Discussion

In this section, the proposed method is evaluated by using various performance metrics. The performance metrics such as accuracy, precision, recall, F1-score, 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 are as formulated in the equations (4) to (7) as follows:
Accuracy: It is the ratio of true positives and true negatives to a total number of classifications.

$$\text{Accuracy} = \frac{\text{True Positive+True Negative}}{\text{True Positive+False Positive+True Negative+False Negative}} \qquad (4)$$

Precision: The ratio of true positive over the classifications of all positive.

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive+False Positive}} \qquad (5)$$

Recall: Proportion of original positives that were correctly classified.

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive+False Negative}} \qquad (6)$$

F1-score: Combines precision and recall giving average value of weight.

$$\text{Recall} = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision+Recall}} \qquad (7)$$

Mean Absolute Error: Mean of absolute difference between the actual value and predicted values. This can be calculated by the below expression

$$\text{MAE} = \sqrt{\frac{1}{m}\sum_{i=1}^{n}} \quad |y_i - \hat{y}_i| \qquad (8)$$

Mean Squared Error: measure an average of the squared error of the predicted value and the actual value. This is always a positive and a risk function. This can be calculated by the below expression

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n} \quad (y_i - \hat{y}_i) \qquad (9)$$

Root Square Error Value: the difference between the predicted values using the estimator and observed values. This can be calculated by the below expression

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}} \quad (y_i - \hat{y}_i)^2 \qquad (10)$$

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 method is evaluated using accuracy, precision, recall, F1-score, MAE and RMSE.

Table 1. Performance analysis of the ResNet101 model with existing models

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
GoogleNet	82.94	81.40	81.45	81.42
MobileNet	87.86	86.34	87.03	86.68
AlexNet	91.86	90.64	89.19	89.90
ResNet50	95.59	95.33	94.08	94.63
ResNet101	99.56	99.40	99.38	99.18

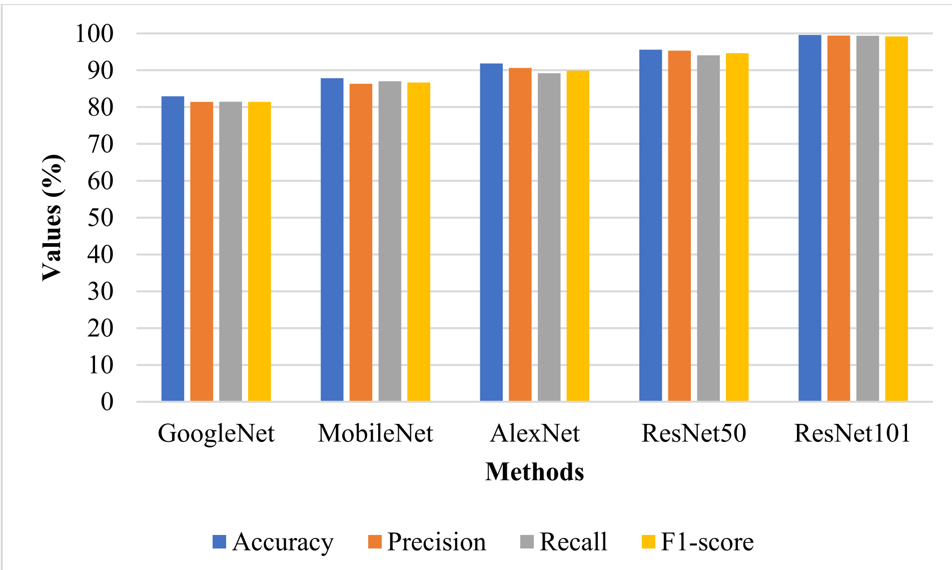

Figure 4. Graphical representation of ResNet101 with existing models

Table 1 and Figure 4 represent the performance analysis of ResNet101 with the existing models. The GoogleNet, MobileNet, AlexNet and ResNet50 are measured and compared with the ResNet101. The obtained result shows that the proposed ResNet101 model achieves better results by using performance metrics like Accuracy, Precision, Recall, and F1-score values of about 99.36%, 99.25%, 98.57%, and 99.18%.

Table 2. Performance analysis of the ResNet101 model with existing models of error values

Methods	MAE	MSE	RMSE
GoogleNet	1.39	2.22	1.49
MobileNet	1.28	2.10	1.45
AlexNet	0.98	0.62	0.79
ResNet50	0.85	0.56	0.75
ResNet101	0.79	0.51	0.72

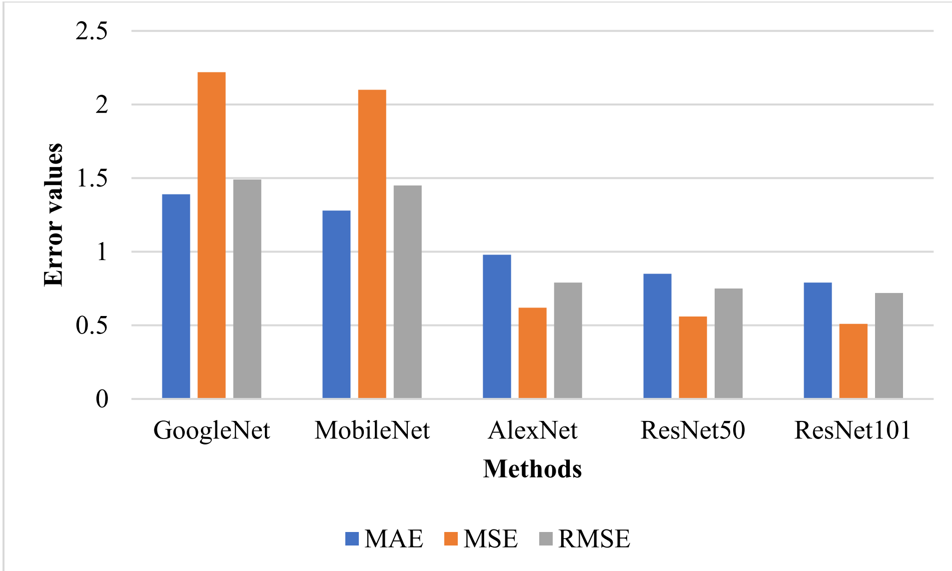

Figure 5. Graphical representation of ResNet101 with existing models

Table 2 and Figure 5 represent the error values of ResNet101 with the existing models. The GoogleNet, MobileNet, AlexNet, and ResNet50 are measured and compared with the ResNet101. The obtained result shows that the proposed ResNet101 model achieves a better result by using performance metrics like MAE, MSE, and RMSE values about 0.79, 0.51 and 0.72 respectively.

Table 3. Performance analysis of Attention based VGG-16 model with existing models

Methods	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
DenseNet	85.87	84.19	83.45	83.73
LeNet	89.23	87.56	86.03	86.88
VGG16	93.79	92.74	91.19	91.26
VGG19	95.32	94.62	93.08	93.69
Attention based VGG-16	99.56	99.40	99.38	99.18

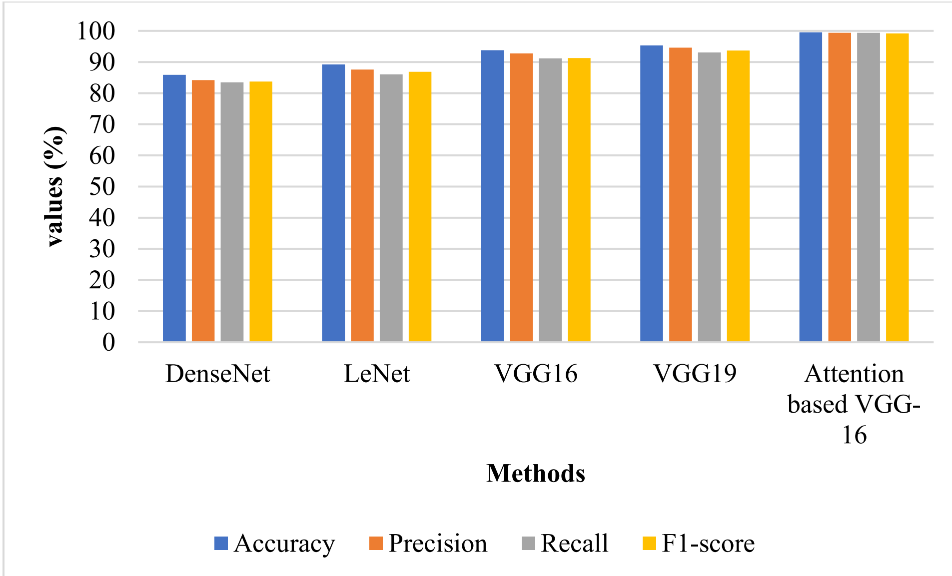

Figure 6. Graphical representation of proposed method with existing methods

Table 3 and Figure 6 represent the performance analysis of the proposed Attention-based VGG-16 with the existing methods. The DenseNet, LeNet, VGG16 and VGG19 are measured and compared with the Attention-based VGG-16. The obtained result shows that the proposed ResNet101 model achieved better results by using performance metrics like Accuracy, Precision, Recall and F1-score values of about 99.36%, 99.25%, 98.57%, and 99.18%.

Table 4. Performance analysis of Attention-based VGG-16 model with existing models of error values

Methods	MAE	MSE	RMSE
DenseNet	1.27	2.32	1.62
LeNet	1.18	2.19	1.48
VGG16	0.98	0.62	0.89
VGG19	0.86	0.56	0.81
Attention based VGG-16	0.79	0.51	0.72

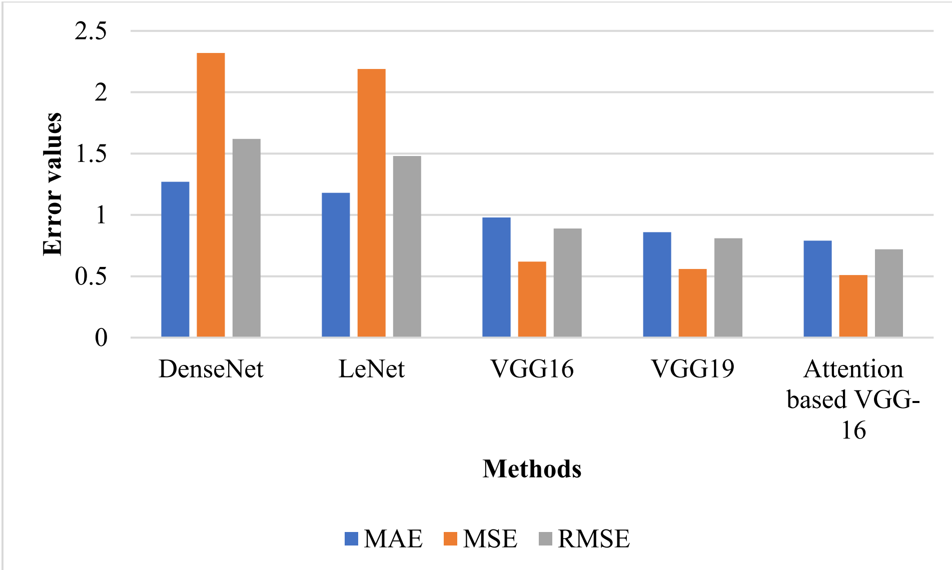

Figure 7. Graphical representation of proposed method with existing methods

Table 4 and Figure 7 represent error values of Attention based VGG16 with the existing methods. The DenseNet, LeNet, VGG16, and VGG19 are measured and compared with the Attention based VGG16. The obtained result shows that the proposed model Attention based VGG16 achieves a better result by using the performance metrics like MAE, MSE and RMSE values of about 0.79, 0.51 and 0.72.

4.2 Comparative Analysis

This section shows the comparative analysis of proposed Attention based VGG16 in terms of method, datasets, accuracy, sensitivity and well as specificity are shown in Table 5. The accuracy, sensitivity as well and specificity of the proposed Attention based VGG16 are more efficient than the existing methods. Table 5 shows the comparative analysis of the proposed method with recent research methods.

Table 5. Comparative Analysis of Proposed method with existing methods

Author	Method	Accuracy (%)	Precision (%)	Recall (%)	MAE
S. Neelakandan *et al*. [16]	OWENN	98.23	N/A	N/A	0.79
Umair Jilani *et al*. [17]	CNN	98.63	99.20	97.73	N/A
Xiaoxu Liu and Wei Qi Yan [19]	Capsule Neural Network	98.72	90.83	91.06	N/A
Proposed	Attention based VGG-16	99.36	99.25	98.57	0.72

4.3 Discussion

Table 5 represents the proposed Attention based VGG-16 performance with existing methods such as OWENN, CNN and Capsule Neural Network with accuracy, precision, recall and MAE. Regarding an accuracy metric, the proposed Attention based VGG-16 obtained 99.36% accuracy, but existing methods of OWENN, CNN, and Capsule Neural Network achieved 98.23%, 98.63%, and 98.72% respectively. These accuracy results are low when compared to the proposed method. Regarding precision, the proposed Attention based VGG-16 obtained 99.25%, but the existing methods of CNN and Capsule Neural Network achieved precision of 99.20% and 90.83% respectively. These precision results are low when compared to the proposed method. Regarding a recall, proposed Attention based VGG-16 obtained 98.57%, but existing methods of CNN and Capsule Neural Network achieved the precision of 97.73% and 91.06% respectively. These recall results are low when compared to the proposed method.

5. Conclusion

In this research, the prediction of traffic signals in urban cities using the classification method of Attention-based VGG-16 is proposed. In this method, the public repository of road traffic prediction IoT dataset is utilized, which is derived from the sensors and cameras and the information collected from the traffic environment. The min-max normalization method is utilized for the enhancement of the dataset and the CNN architecture of ResNet101 is utilized for the extraction of the feature. The VGG-16 architecture is a classification algorithm, mostly utilized for image classification and prediction. An Attention-based VGG-16 algorithm is used for the classification of the traffic signal with the Intel 80286 microprocessor. The proposed model’s performance is evaluated by the number of performance metrics and it achieves 99.36% accuracy, 99.25% precision, 98.57% recall and 0.72 MAE respectively when compared to the existing methods such as OWENN, CNN and Capsule Neural Network. In the future, this proposed method will extend to solve the data imbalance issues to improve the accuracy of results.

References

Lee, W.H. and Chiu, C.Y., Design and implementation of a urban traffic signal control system for smart city applications. *Sensors*, *20*(2), p.508, 2020.

Arifin, A.S. and Zulkifli, F.Y., Recent development of smart traffic lights. *IAES International Journal of Artificial Intelligence*, *10*(1), p.224, 2021.

Fadda, M., Anedda, M., Girau, R., Pau, G. and Giusto, D.D., A social internet of things smart city solution for traffic and pollution monitoring in cagliari. *IEEE Internet of Things Journal*, *10*(3), pp.2373-2390, 2022.

Fadda, M., Anedda, M., Girau, R., Pau, G. and Giusto, D.D., A social internet of things smart city solution for traffic and pollution monitoring in cagliari. *IEEE Internet of Things Journal*, *10*(3), pp.2373-2390, 2022.

Saleem, M., Abbas, S., Ghazal, T.M., Khan, M.A., Sahawneh, N. and Ahmad, M., Smart cities: Fusion-based intelligent traffic congestion control system for vehicular networks using machine learning techniques. *Egyptian Informatics Journal*, *23*(3), pp.417-426, 2022.

Jafari, S., Shahbazi, Z. and Byun, Y.C., Designing the controller-based urban traffic evaluation and prediction using model predictive approach. *Applied Sciences*, *12*(4), p.1992, 2022.

Ramesh, K., Smart Traffic Prediction and Congestion Reduction in Smart Cities. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, *12*(12), pp.1027-1033, 2021.

Jafari, S., Shahbazi, Z. and Byun, Y.C., Improving the road and traffic control prediction based on fuzzy logic approach in multiple intersections. *Mathematics*, *10*(16), p.2832, 2022.

Omar, A., AlMaeeni, S., Attia, H., Takruri, M., Altunaiji, A., Sanduleanu, M., Shubair, R., Ashhab, M.D.S., Al Ali, M. and Al Hebsi, G., Smart city: Recent advances in intelligent street lighting systems based on IoT. *Journal of Sensors*, *2022*.

Dhingra, S., Madda, R.B., Patan, R., Jiao, P., Barri, K. and Alavi, A.H., Internet of things-based fog and cloud computing technology for smart traffic monitoring. *Internet of Things*, *14*, p.100175, 2021.

Navarro-Espinoza, A., López-Bonilla, O.R., García-Guerrero, E.E., Tlelo-Cuautle, E., López-Mancilla, D., Hernández-Mejía, C. and Inzunza-González, E., Traffic flow prediction for smart traffic lights using machine learning algorithms. *Technologies*, *10*(1), p.5, 2022.

Lilhore, U.K., Imoize, A.L., Li, C.T., Simaiya, S., Pani, S.K., Goyal, N., Kumar, A. and Lee, C.C., Design and implementation of an ML and IoT based adaptive traffic-management system for smart cities. *Sensors*, *22*(8), p.2908, 2022.

Tian, Y., Abnormal Traffic Prediction and Classification based on Information Big Data. *Highlights in Science, Engineering and Technology*, *23*, pp.145-153, 2022.

Lohrasbinasab, I., Shahraki, A., Taherkordi, A. and Delia Jurcut, A., From statistical-to machine learning-based network traffic prediction. *Transactions on Emerging Telecommunications Technologies*, *33*(4), p.e4394, 2022.

Li, P., Zhang, Y., Zhang, K. and Jiang, M., The effects of dynamic traffic conditions, route characteristics and environmental conditions on trip-based electricity consumption prediction of electric bus. *Energy*, *218*, p.119437, 2021.

Neelakandan, S.B.M.A.T.S.D.V.B.B.I., Berlin, M.A., Tripathi, S., Devi, V.B., Bhardwaj, I. and Arulkumar, N., IoT-based traffic prediction and traffic signal control system for smart city. *Soft Computing*, *25*(18), pp.12241-12248, 2021.

Jilani, U., Asif, M., Rashid, M., Siddique, A.A., Talha, S.M.U. and Aamir, M., Traffic congestion classification using GAN-Based synthetic data augmentation and a novel 5-layer convolutional neural network model. *Electronics*, *11*(15), p.2290, 2022.

Niu, C. and Li, K., Traffic light detection and recognition method based on YOLOv5s and AlexNet. *Applied Sciences*, *12*(21), p.10808, 2022.

Liu, X. and Yan, W.Q., Traffic-light sign recognition using Capsule network. *Multimedia Tools and Applications*, *80*, pp.15161-15171, 2021.

Chen, H., Hu, S., Hua, R. and Zhao, X., Improved naive Bayes classification algorithm for traffic risk management. *EURASIP Journal on Advances in Signal Processing*, *2021*(1), pp.1-12, 2021.

Zhao, R., Yin, J., Xue, Z., Gui, G., Adebisi, B., Ohtsuki, T., Gacanin, H. and Sari, H., An efficient intrusion detection method based on dynamic autoencoder. *IEEE Wireless Communications Letters*, *10*(8), pp.1707-1711, 2021.

Bharadiya, J.P., Convolutional Neural Networks for Image Classification. *International Journal of Innovative Science and Research Technology*, *8*(5), pp.673-677, 2023.

Rafiq, A., Imran, M., Alhajlah, M., Mahmood, A., Karamat, T., Haneef, M. and Alhajlah, A., Deep Feature Extraction for Detection of COVID-19 Using Deep Learning. *Electronics*, *11*(23), p.4053, 2022.

Muhtasim, D.A., Pavel, M.I. and Tan, S.Y., A patch-based CNN built on the VGG-16 architecture for real-time facial liveness detection. *Sustainability*, *14*(16), p.10024, 2022.

AATILA, M., LACHGAR, M., HRIMECH, H. and KARTIT, A., Diabetic retinopathy classification using ResNet50 and VGG-16 pretrained networks. *International Journal of Computer Engineering and Data Science (IJCEDS)*, *1*(1), pp.1-7, 2021.