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An Adaptive Traffic Light Control System Based On Artificial Intelligence

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Abstract:

The phenomenon of traffic congestion is one of the most widespread phenomena in the world, especially in developed countries where the number of vehicles is increasing, which means that many traffic jams occur in the streets, especially at times when employees go to and from work, which is known as peak times and is concentrated usually in the early morning, and this gives a great feeling of annoyance and boredom as a result of wasting hours of time in the streets, and being late for work because of not being able to reach it at the appropriate time. Add to that a signal system traditional traffic, which played a prominent role in these bottlenecks, can no longer smooth management and organization of traffic, because it did not develop with the development of cities. From this point of view, studied and applied, a system based on image processing that uses the technology to detect objects in the image by removing impurities, and thus determining the traffic density based on the number of objects. In the picture, which represents the vehicles, the traffic lights were controlled depending on the traffic density on each road. The proposed system is implemented using MATLAB R2021 language, and for performance evaluation, classification accuracy is used as the evaluation metric. On traffic lots (MTID) the data set is frames of video recorded at 40000 (frames per second) FPS and taken by a drone. The Multi-view Traffic Intersection Dataset is used in the proposal system, it is available on "https://www.kaggle.com/datasets" . Categories: Bicycles, Cars, Buses, Trucks. To test the effectiveness of the proposed approach. Three pre-trained networks (AlexNet, ResNet, and DenseNet) were implemented. Using the ResNet50 model resulted in a significant improvement in performance. In particular, the proposed system using ResNet50 achieves an accuracy average of 99.47% on the (MTID) datasets respectively.

Keywords: Deep learning; Convolutional Networks; Traffic; Cnn; DenseNet; AlexNet; Resnet50

1-Introduction

Many areas, especially those with growing populations and big cities, have serious problems with traffic control and management.Traffic lights use time division multiplexing to lessen traffic at intersections[1]. Fixed-cycle controllers are used at all signalized intersections in a number of different countries. The only drawback of utilizing a traffic light is that it takes longer to get where you're going(stop time or waiting time). An intersection's delay serves as a performance measure for the effectiveness of a traffic signal controller. The phases, timing, and order of traffic signals affect how well traffic moves through an intersection. The controller of adaptive signals is in charge of timing, sequence, and phases[1]. The timing and arrangement of traffic signals need to be optimized in order to reduce traffic congestion. From the perspective of computer vision, traffic surveillance is particularly difficult because of the abundance of various scenes, objects, and, in particular, objects that overlap and cause occlusion. The simplest method of preventing occlusion is to strategically place your sensors. The sensors are typically positioned as high as possible on either temporary or transportable poles or on already-existing infrastructure, such as traffic light poles, in an effort to accomplish this[2]. The traffic light timing used by the current system controls traffic flow. However, a lot of research is being done to replace the current traffic light system with an automated and adaptive one in order to address the issue of traffic congestion. A few researchers employed sensors and radio frequency identification. Hardware to determine how packed the cars are, but putting this into practice is costly and challenging. In order to determine the vehicle density, some researchers are also attempting to solve the issue through image processing and the image subtraction method [1-4]. In the image subtraction method, they have employed a fixed, unchangeable reference image. However, this approach is ineffective at night because the lighting conditions differ from those during the day. The computed density is used to inform the decision-making process when changing the traffic light[3]. It is widely acknowledged that optimizing traffic signal control yields the greatest benefits in terms of decreasing traffic on surface streets, and that real-time adaptive control strategies have the greatest room for improvement[4]. When a traffic signal like this isn't independent of every other traffic signal nearby, their suggested methodology's premise will no longer be the best one. Their values, which were provided to the machine learning model, do not take into consideration the size of the lines or the amount of time spent in them. In the event that the outgoing lanes were blocked, traffic exiting the traffic signal would therefore have to wait in a queue in the lane before leaving the traffic signal. In such cases, their model was unable to deliver the best possible outcome. The suggested techniques are adaptable enough to be used with networked traffic signals[5]. This study is divided into two primary sections: an image processing model for the collected data, and a CNN model for result prediction that takes into account feature selection, and neural network model training. The hallways are watched over and photos are taken with cameras. Image processing is used to identify and count the number of vehicles in each direction as well as the length of the queue. The CNN module receives data coming from all directions. The trained model will calculate the route and time limit that must be allowed for the green phase based on the number of vehicles.

2- Background and related work:

Alfonso Navarro-Espinoza et al. [9], This work presents algorithms for both deep learning (DL) and machine learning (ML). This paves the way for adaptive traffic control, which can be implemented via an algorithm that modifies timing in accordance with predicted flow or by remotely controlling traffic lights. As a result, the only subject of this work is traffic flow prediction.Two publicly available datasets are used for training, validating, and testing the proposed ML and DL models. The first one displays the total number of cars sampled over a 56-day period at six intersections every five minutes using different sensors. Four out of the six intersections are used in this study's ML and DL model training. The next best option was Multilayer Perceptron Neural Network (MLP-NN), which was followed closely by Gradient Boosting, Random Forest, Linear Regression, and Stochastic Gradient, which produced better results (R-Squared and EV score of 0.93) and required less training time. Recurrent Neural Networks (RNNs) also produced good metrics results but required a longer training time. All ML and DL algorithms achieved good performance metrics, indicating that it is feasible to deploy them on smart traffic light controllers.

Muhammad Saleem et al. [10], this study proposed a fusion-based intelligent traffic congestion control system for VNs (FITCCS-VN), which gathers traffic data and routes traffic on available routes using machine learning (ML) techniques in order to reduce traffic congestion in smart cities. By providing drivers with state-of-the-art services that enable them to remotely view traffic flow and the number of vehicles available on the road. The proposed system seeks to prevent traffic jams, it improves traffic flow and reduces congestion. It offers a 95% accuracy rate and a 5% miss rate as comparison to previous methods.

Dex R. ALEKO et al. [11], this paper aims to assist traffic management authorities in effectively addressing traffic congestion in cities by proposing a new Adaptive Traffic Light Control System (ATLCS). Our ATLCS's primary function is to synchronize multiple traffic lights that control successive junctions by delaying the moments when each light turns green in a specific direction. Vehicles departing the city center can therefore go farther without stopping (reducing the frequency of the "stop and go" phenomenon), which shortens the distance they must travel. Depending on how many cars are waiting at each intersection, this type of delay is dynamically updated. Comparing our ATLCS to non-synchronized fixed time traffic light control systems, we find that the average travel time of vehicles traveling in the synchronized direction has been significantly reduced (by as much as 39%).Moreover, the simulated road network as a whole saw an improvement of 17%.

Chuanxi Niu et al. [12], this paper suggests an approach based on AlexNet image classification and YOLOv5 object detection model. It adopts the principle of first detection, then classification. YOLOv5s are used to first identify the traffic light area, which is then extracted and subjected to image processing before being fed to AlexNet for recognition assessment. The low recognition rate of the single-target detection algorithm for small-target detection can be circumvented with this method. Given that the homemade dataset has a higher proportion of low- light images (The Zero- Deep Curve Estimation) ZeroDCE low-light enhancement algorithm is used to optimize it. On the traffic light recognition dataset, the network model trained after this optimization can achieve an average accuracy of 87.75% and an (average precision) AP of 99.46%, which is 0.07% higher than the pre-optimization performance.The outcomes of the experiment demonstrate that the method can recognize a wide variety of traffic lights with a high accuracy rate.

Research methodology:

The purpose of this study is to create an effective traffic system to detect traffic congestion based on deep learning algorithms to classify vehicle density using CNN networks that are trained on four degrees of congestion images. The outputs of this network are to predict the four degrees of congestion and redistribute the time allocated to the four directions.

3- The Proposed System:

The proposed system consists of three phases:

1- Preprocessing

2- Convolutional neural network

3- System Application

The system uses traffic intersection monitoring camera installed in the traffic intersection. Preferably, it should be at the light pole's height to prevent obstruction. The system receives an image from these cameras once every second as an input. Views from all four sides of the manually preset traffic intersection are included. The system divides the images into four sides before sending them to the CNN network, which was trained on four degrees of crowding images beforehand. The output of the CNN network is Predicting the four degrees of crowding and redistributing the time allocated to the four sides. The busiest side will have 100% of the time allocated for it, while the least crowded side will have 50% of the time allocated for it, and the least and then the least will have 25% and 0% of the time allocated if there is no crowding.

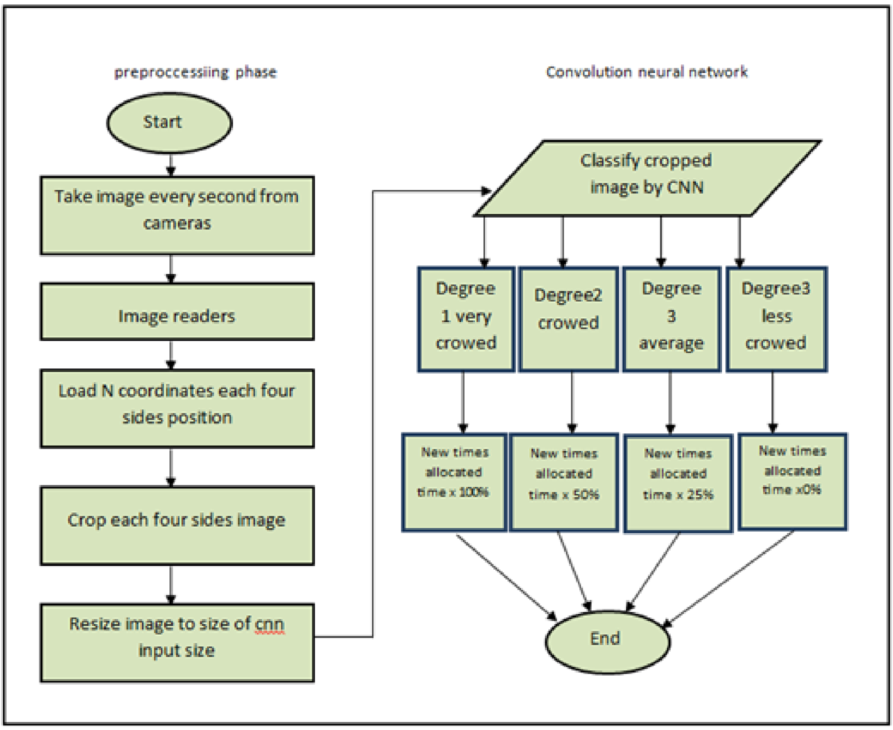


Fig (1): The block for the proposed system

3.1-Pre Processing Stage:

Prior to the input image being utilized in the suggested system, pre-processing is performed on it, as illustrated in Figure 2. These steps include the following:

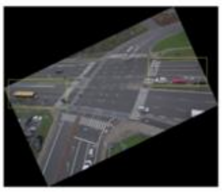
step 1: Obtain an image of the position from the cameras.

step 2: Determine the coordinates of the four side of traffic intersection.

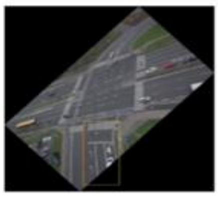
step 3: cropped the images of four side.

step 3: Rotation and alter the cropped image's size in accordance with the system's chosen algorithm.

a- The camera equips the system with images



b- Determine the coordinates of the individual parking lot



c- Crop individual positions

Fig (2): a,b,c Clarify Pre Processing Stage

3.2- Convolution neural network phase:

The CNN AlexNet was utilized in this study to assess the traffic condition and determine whether it is empty or congested after all pre-processing of the traffic image was finished.

3.2.1- CNN layers:

The three different types of layers in CNN are arranged in a sequential fashion, with each layer carrying out a distinct function.

I- The Convolutional layer: - it is utilized to produce feature maps, which highlight the distinctive aspects of the original image. As its name suggests, the convolution layer's function is entirely distinct from that of the neural network's other layers; instead, it consists of filters that convert images into feature maps[10]. As an illustration Figure 3 illustrates how the convoluted image is calculated [11], if the kernel filter (K) and the input image (I) are both 2D types.

$$\mathbf{S(I\ ,j)=\sum_{m}\sum_{n}I(m\ ,n)K(\ I\ -m,\ j-n)} \qquad \mathbf{(1)}$$

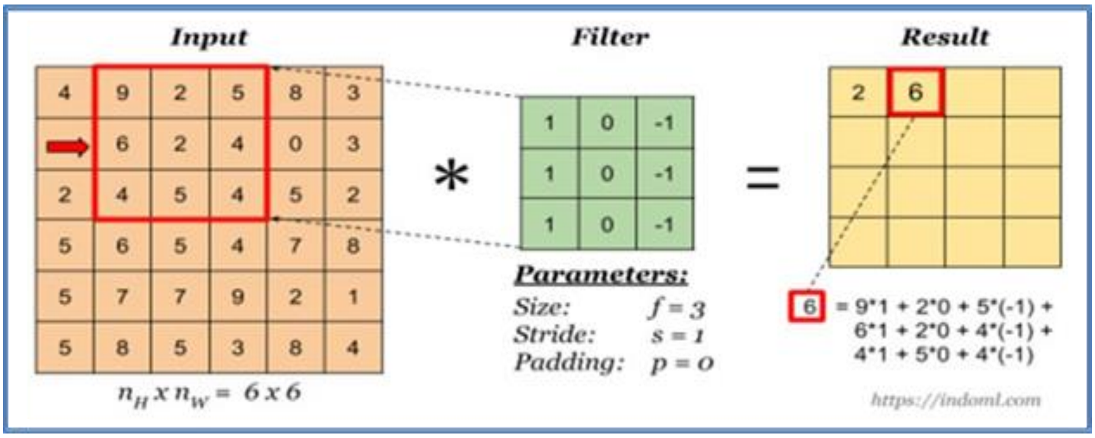


Fig (3): Element-wise matrix multiplication in the convolutional layer [11]

II- Pooling layer (subsampling layer): As soon as the torsion process is finished, dimensional reduction is carried out. As a result, the parameter set is reduced, which in turn shortens the training period and minimizes over-processing [12]. It contributes to keeping both the input and output maps in their current states. This process's creation is described [13]

$$X_j^i = \text{down}(\ X_j^{i-1}\ ) \qquad \mathbf{(2)}$$

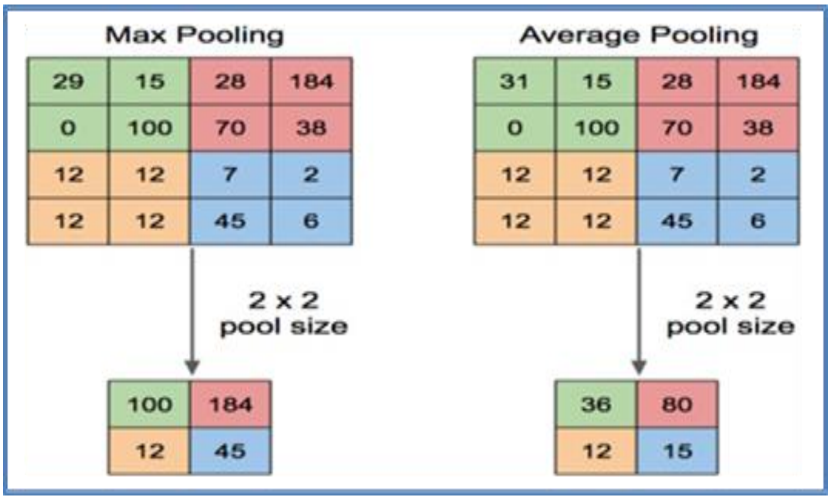


Fig 4: Displays two different assembly methods [11].

III -Fully connected layers: The final output of the CNN layer is sent to the classification layer (fully connected network) as payment [13], [14]. A fully linked layer uses features from the previous layer (the Pooling layer) to calculate the results for each class. The classification layer makes use of the fully connected and forward neural layers [13].

3.2.2- AlexNet

Also referred to as a transfer learning model, this approach teaches knowledge through extensive data training. Three fully-connected layers (FC), three maximum aggregation layers, and five convolutional layers make up AlexNet. It was the inaugural ILSVRC 2012 competition winner [15]. Fig. 2 displays an example of the AlexNet architecture.

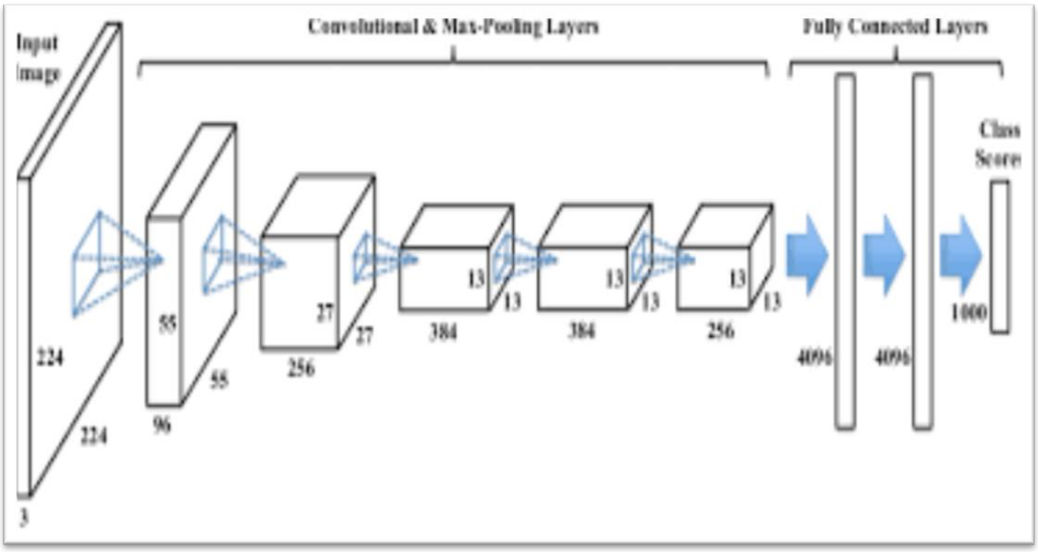


Fig 5: Schematic diagram of AlexNet layers [16-14]

3.2.3-Training of AlexNet

In this section of the study, AlexNet was trained using random samples and a change rate of 60% - 90% of the data for training and 40% - 10% for testing. Table (4.1) displays the training results. Based on the outcomes shown in Table (4.1), the data were divided into two groups. Using random sampling, these are the test data (20%) and training data (80%). Training was completed in full during elapsed time 7 min and 13 sec. The AlexNet training result is displayed in figure (6).

Table (1): Accuracy according to the division of training data into the test AlexNet

NO.	Training data ratio	Test data ratio	Accuracy of data MTID
1	60%	40%	97.51%
2	70%	30%	97.57%
3	80%	20%	97.65 %
4	90%	10%	99.68%

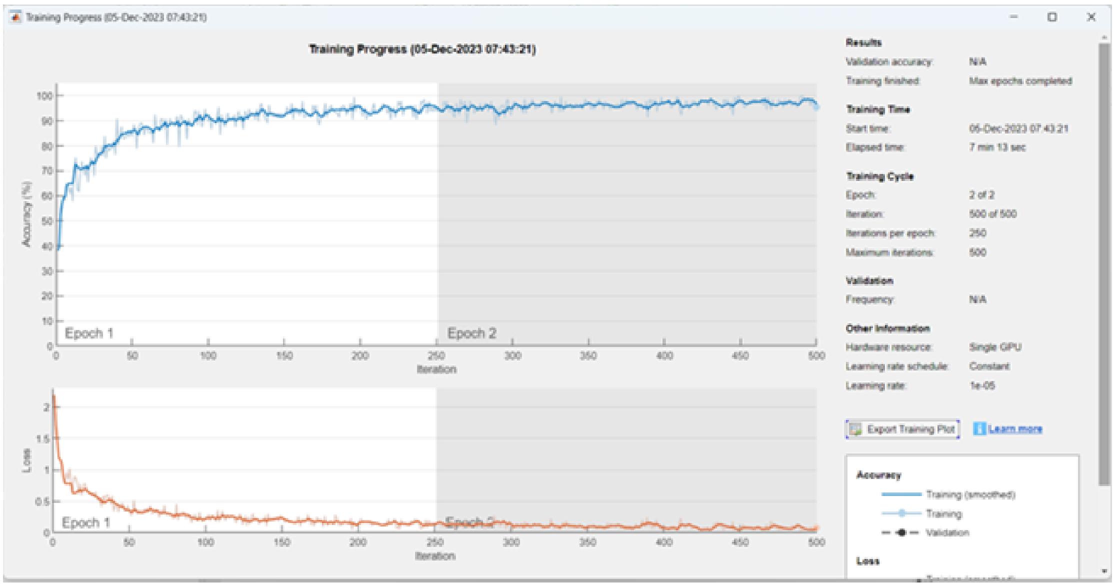


Figure (6): The result of training the AlexNet model

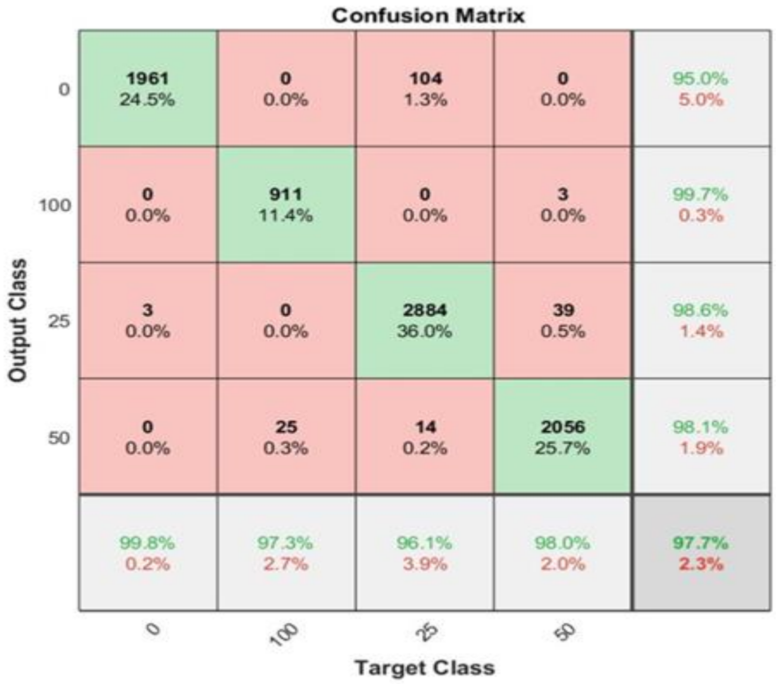


Figure (7): The confusion matrix of testing data(20%) on AlexNet model

3.2.3- Test AlexNet Results

As mentioned earlier, the testing process starts right after the training ends. Samples that are (20%) of the MTID dataset and the dataset are tested on the AlexNet models that we trained previously AlexNet model achieved performance with an average accuracy of 97.65% rate on the MTID dataset.

4- Datasets: In this study, the MTID data set was used.

5- Evaluation criteria:

Several metrics were employed to assess the suggested system, including measure F, recall, accuracy, precision, and second [17]. The equations' symbols denote that the number of sub-images that are classified as occupied and are in fact occupied True Prediction (TP), the number of unoccupied sub-images that are classified as unoccupied True Negative (TN) and the number of sub-images that are classified as occupied but are not in fact occupied False Prediction (FP) are known as true positive and false positive, respectively. False Negative, or FN, is the number of sub-images that are marked as unoccupied but are actually occupied.

$$Accuracy = \frac{TP+TN}{P+N} \quad (1) \qquad\qquad Precision = \frac{TP}{(TP+FP)} \quad (2)$$

$$Recall = \frac{TP}{(TP+FN)} \quad (3) \qquad F\text{-}score = \frac{2\times Precision \times Recall}{Precision+Recall} \quad (4)$$

6- Implementation details:

Following the completion of the training, the testing process starts. While 80% of samples (40000 images) were randomly chosen for training AlexNet during the training stage, The CNN classifier that was developed during the training process—traffic image—is the one that is tested on recently unclassified images. The traffic image is then listed as empty or congestion. To conduct the suggested CNN performance test, a random selection 20% of the total samples, was made. At this point, comparisons between the results and the original images are also used to establish benchmarks. On a PC with MSI specifications, such as an Intel(R) Core (TM) i7-10750H @ 2.60 GHz CPU, Windows 11 Home, 16 GB of RAM, a 64-bit operating system, and a GPU (RTX3060), AlexNet was easily trained and tested using all CNN codes.AlexNet is based on the MATLAB R2021a language.

7- Evaluation results:

Using forty thousand images taken at different times of the day from the MTID dataset, we have achieved 99.47% accuracy using the proposed regime. Additionally, our suggested system achieved 100% accuracy when applying knowledge gained from local database images that the network was not exposed to, using an ResNet50 network trained on the MTID dataset.Table (2) MTID dataset-based primary classification criteria.

Table (2): The model classification criteria's proposed results.

Evaluation criteria	MTID dataset
Accuracy	99.47 %
precision	99.49 %
Recall	99.49 %
F-measure	99.49 %

Table (3): Comparison of the results of the proposed system with other deep learning based traffic light models.

References	Model	Recognition Accuracy
		MTID dataset
Muhammad et al. (2022) in[10]	FITCCS-VN	95%
Chuanxi.et al. (2020) in[12]	YOLOv5's	87.75%
CHENG et al. (2022) in[13]	CFNN	90.45%
The Proposed System (2024)	**Resnet50**	**99.47 %**

8- Conclusion

In The study, we evaluated develops an image-based framework that uses a pre-trained deep CNN to identify car traffic jams in an outdoor environment. On the publicly available training dataset (MTID dataset), The framework's high accuracy of 99.47% indicates that it is appropriate for use in scenarios where it can provide a dependable and reasonably priced solution. This indicates that the AlexNet algorithm-based suggested system was effectively detecting the locations of traffic jams caused by cars. Nevertheless, there are certain obstacles that restrict the effectiveness of transfer learning. These include unfavorable weather conditions like fog, rain, and dust, which alter image lighting, the quantity of cars that obstruct the view, and the bias in the training data that is used.

9- Future work

1- Building a system to detect congestion at a traffic intersection that works in real time, in which the camera is focused and takes the frame directly and feeds it to previously trained networks. It detects congestion and works on dividing the time.
2- The proposed system includes identifying ambulance, emergency, and fire vehicles and opening traffic directly for them.
3- A system that detects the numbers of violating vehicles and informs the traffic system to take the necessary legal measures against them.

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