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Smart System for Emergency Road Lane Utilization

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Abstract. *Increased vehicle traffic, and overburdened public infrastructure are all factors affecting for emergency vehicles such as ambulances which must arrive as quickly. The proposed system performs a set of tasks including creation smart road used for emergency vehicles, the proposed system works to detect the vehicle based on YOLOV4 and Convolutional Neural Networks (CNN) using (VGG16-Resnet50) for classification. the network algorithm (VGG16) achieved accuracy of vehicle classification up to (99.87%) and (Resnet50) achieved an accuracy up to (97.68%).*

Keywords: VGG16, Resnet50, YOLOV4, vehicle detection**.**

Introduction

Many people die in road accidents, heart attacks and another emergency cases throughout the world as a result of ambulance delays or delay in reaching hospitals due to traffic congestion and Seek medical assistance. The first hour following an emergency is important for doctors to assist a patient in saving their life. As an example if a person experiences a heart attack and receives competent medical treatment and attention within the first hour of the event, their chances of survival and recovery improve significantly [1]. The golden hour is the first hour following a heart attack. The loss of a considerable volume of blood is one of the most prevalent causes of mortality in car accidents, as a result, it was necessary to enhance the ambulance's quick arrival to hospitals as well as the accident scene, and AI-based systems might be utilized to prioritize the ambulance over any other vehicle because life is so valuable [2]. The Deep Learning Model is one of the machine learning techniques. It's a form of Artificial Neural Network that has numerous layers between the input picture data and classification output. These layers are linear or nonlinear functions that extract key messages from data. Layers come in a variety of architectures, such as convolutional, pooling, and completely linked, depending on their individual performance. Neural networks have a long history as a machine learning design, dating back to the 1980s. However, it wasn't until the early twenty-first century that graphics processing unit (GPU) were used to create neural networks. The processing power required for the development of Neural Networks is the main roadblock. It normally takes millions of parameters to be computed repeatedly in order for a Neural Network to be fully trained [3]. Each convolutional layer in a Deep Convolutional Neural Networks (DCNN) gathers features from the data and learns abstract information from it; the deeper the network, the more generic the information learns. To increase model fidelity, most recent DL designs use network deepening. However, for optimal performance, the deep web requires a large amount of data. Deepening networks can generate overload in circumstances when data availability is limited. As a result, the aim of acquiring generic features will be unattainable [4]. The objective of this paper is to design a smart road system that is intended for use by emergency vehicles (ambulances), and the road is monitored with CCTV cameras, where the proposed system works to detect objects (vehicles) and in the event that the driver of the vehicle (unlicensed) uses the emergency road, the proposed system takes a picture of the vehicle and is done determined as a violation vehicle. The system uses a set of libraries available in Python, use pre-trained network YOLOV4 for vehicle detection, and we used deep learning of Convolutional Neural Networks (CNN) and transformation Learning (VGG16-Resnet50) for vehicle classify (truck-ambulance), where Convolutional Neural Networks (CNN) have been trained on transfer learning. On a data set containing (8310) images (4155 ambulances and 4155 vehicles) divided into two groups, the first group is the training data set (90%) of the data, and the second group is the test data (10%), after conducting training process for aforementioned neural networks.

Related works

Many researches have been conducted on the issue of the smart road for emergencies, including:

In 2015, Parthasarathi et al. proposed an intelligent traffic system to give emergency vehicles greater priority in the flow of traffic. an infrared detector has been used to determine the density of cars, and the distance between both red and blue is calculated. Pictures were taken from the highest point on the road. The images are converted to grayscale images and then subjected to processing. [5]

In 2016, Nellor et al. They introduced a system that uses a camera to measure the distance between an emergency vehicle and a Traffic Management Center (TMC) alert. After applying several morphological procedures to each image, they used different techniques to determine the distance between the camera and the emergency vehicle. The distance, speed and data change statistics are then more efficiently provided to the emergency vehicle's traffic light control center [6].

In 2020, VAN-THUAN and WEI-HO propose a system that uses the sound of a siren to automatically recognize an emergency vehicle. Implemented experiments on a range of datasets to recognizing siren sound with the help of a convolutional networks (CNN). An efficiency of (96.89) percent even for samples as brief as (0.25) seconds [7].

In 2020, Kaushik S and others used object detection system to detect vehicles in emergency situations, which is the Faster R-CNN algorithm for object detection and the Mask R-CNN algorithm for classifying and using data of up to 400 images of emergency vehicles. This application achieved an accuracy of (82%) for the classification of the mechanism and (74%) for detecting about [8].

In 2021, Muhammad Akmal et al. designed a system to detect emergency vehicles to enable them to reach them quickly. The applied convolutional networks (CNN) was using to classify images of emergency car on the way. This work was used as a pre-trained model with a low convolutional layer VGG-16 based on this work. On the experiment, the proposed method obtained an accuracy of (95%) [9].

Proposed System Assumption and Design

The proposed system will do defining a lane as part of a private public road for use by licensed vehicles (ambulances) and other vehicles are not allowed to use the road. placing traffic lights on the side of the road to alert drivers not to use the lane. Use of analytical video cameras (IP camera) for the purpose of detecting vehicles, the resolution used in photography is (1920 * 1080) at (25) frames per second. In case of using emergency path, the system detects a vehicle, then classifies it. According to the type of vehicle, the system reports a violation or not. The unlicensed vehicle will be captured and reported to nearest police patrol or traffic police center. The system detects the mechanism when the vehicle body completely exceeds the specified line on the street, then the system calculates the number of tires (the tolerance), after which the system takes a picture of the mechanism and considers it a violation. The street a high-efficiency lighting system. The camera installed at a height of (5 meters) and at a distance of 2 meters from the beginning of the width of the street designated for emergency, and it must be fixed. The system recognizes ambulances and considers them licensed, and other cars considered unlicensed. The mask used in the street to determine emergency path of the line is calculated from the beginning of the street view from the right side. A pre-trained network YOLOV4 algorithm to detect cars has been applied. A VGG16, ResNet50 convolutional neural network was trained to classify vehicle type.

Implemented module

Our system was implemented on a laptop with the specifications, Intel core I5 processor of the 4th generation, RAM (12GB), Intel HD graphics 4600 internal size (2GB).

Object detection

Detecting emergency vehicle items is the initial stage.

The major function of object detector is to train the vehicle detector, which will only produce images of cars, to determine whether or not there is an ambulance. The pre-trained network YOLOV4 network was utilized. It is one of the quickest object detection algorithms, and it is dedicated to the detection method is rapid in the photos of the model that will be built from CCTV video [10]. They used a thick block to form a deeper and more complicated network. After batch and ReLU normalization, there are many convolutional layers, followed by convolution. Furthermore, a dense network is created by connecting numerous thick blocks with transitional layers. Then, using a cross-sectional partial (CSP), split The input feature for dense blocks is split into two pieces, one of which travels straight to the next transitional layer and the other of which passes via dense block [11]. The computation needs are reduced since just one portion goes through the thick block. They utilized CSPDarknet-53 and Darknet-53 from the previous YOLOv3 to extract Backbone's features, which improve CSP connections. Spatial hierarchical clustering (SPP) is used as a solution over CSPDarknet-53 because it improves the receptive field, describes the most essential feature, and does not cause a delay [12]. The probability from each class on which the model is trained is referred to as class probability. The COCO dataset was used to train the form in this scenario. There are (80) opposed categories in this paper. As a result, the class score indicates an (80) percent chance of anything happen in 'Truck' and 'car' are two related categories in the COCO dataset. All photos in this category will be fed into a convolutional neural network to determine whether or not they are emergency vehicles (ambulances).The suggested system is set up using the algorithm steps below [13].

Object detection steps:

1-inserting the video from camera to the system.

2-Choosing the target region.

3- Enter the target area into YOLOV4.

4- Resize frame (416*416).

5- Vehicle detection.

6- Bounding vehicles by rectangular area.

7- Rectangle vehicle movement tracking.

Object recognition

After completing detection process, the image is entered into the convolutional neural network to perform a classification. Two types of transfer learning convolutional neural networks (VGG16-Resnet50) were trained on the data of images of ambulances and other Truck.

VGG16

VGGNet features an extremely deep network that comprises (16) or more CONV/FC layers, are (13) convolutional layers, two fully connected layers, and one SoftMax classifier, and is a model that is commonly used for machine learning [14]. The VGG-16 architecture built a fully connected 16-layer convolutional network. To keep things simple, only three (3x3) convolutional layers were placed on top of one another. First convolutional layers and second of the convolution layers of the VGG-16 network are made up of (64) features kernel filter with a volume of (3x3), as illustrated in Figure 1. As the image input (RGB images with the depth 3) travels through the first and second convolutional layers, its dimension change to (224*224*64). With a stride of two, output is directed a max pool layers. The filter size (124) features kernel filter (3^{rd}–4^{th}) convolution layers is (33 percent). The output is reduced to (56x56x128) using a max pooling layer with stride 2 after these two layers [15]. The 5th, 6th, and 7^{th} levels are the most difficult, convolutional layer with a kernel size of (3x3) are utilized. All three make use of (256) feature maps. A stride (2) max pool layer follows this layer. Convolutional layers are divided into two types: one with a (3x3) kernel size and other by a kernel size of twelfth. Each of these convolutional layer sets has (512) kernel filter. Following this layer is a max-pool with a result was obtained of one. (14^{th} -15^{th}) level is completely connect (4096-unit) After that, there's a (1000-unit) SoftMax output layer (sixteenth layer) fig.1 shows macro-architecture of VGG-16. [16]

Data augmentation

To boost performance and avoid leakage, increasing image data is a common strategy. The Keras libraries' Picture Data Generator class allows use to image data augmentation to suit models. The Generator turns file image into preprocessed tensor that may be immediately input into the train dataset to train a model using different picture rotation, scale, crop, and flipping parameters [17].

ResNet50

ResNet is a good neural network used in a number of computer vision applications, and ResNet50 has 50 layers. It is a short term for Residual Networks. In 2015, this model won first place in the ImageNet competition. ResNet was a game-changer because it made it possible to train 150-layer deep neural networks with ease [18]. The gradient fading problem made training very deep neural networks difficult before ResNet. The idea of a skip connection was initially proposed by ResNet. In this case, skip connections are critical for two reasons: they avoid the gradient fading problem by enabling the gradient to flow down this second shortcut path. It enables the model to know the identity function which ensures that the top layer performs at least as much as the bottom layer [19].

Dataset

The custom vehicle dataset consists of (8310) images (4155 truck images, 4155 ambulance images), all collected from Internet. The dataset was divided into the first set, the training set, and we gave it (90%), and the second set was the test set which was given (10%) of the data set used in this proposed system, work of the vehicle recognition system shows in (fig. 2) [20].

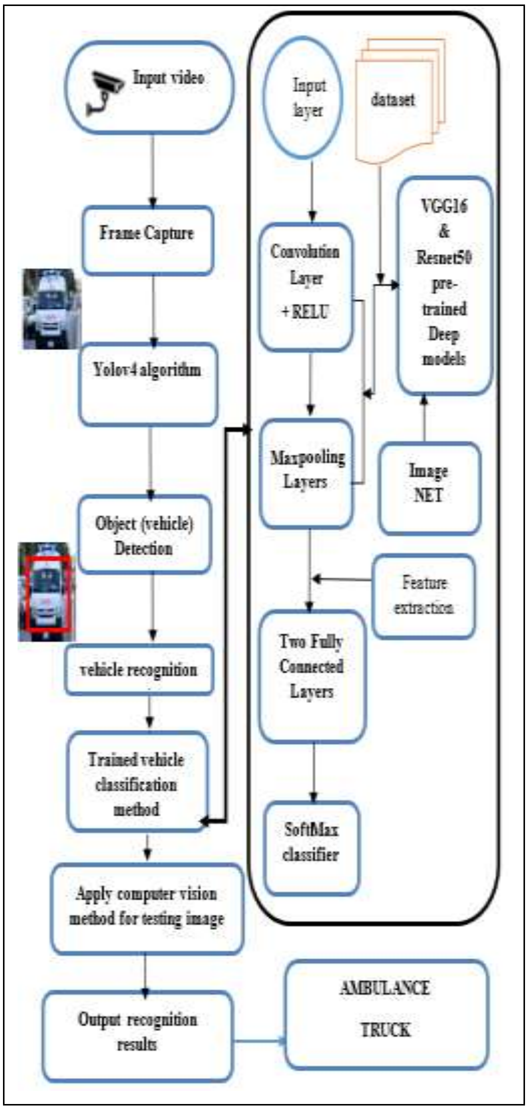

Fig.2. vehicle recognition system is depicted in this flowchart

Experiment Analysis and Results

1- Dataset

The dataset, which consists of approximately (8310) images of vehicles and ambulances, was obtained from Internet. Data is randomly distributed and divided into three categories: training and verification. According to computer specifications, training data will be separated into two parts, and we will integrate pre-trained architecture with the training model, example of image dataset shows in (fig 3).

Fig3. Example of Image Dataset

2- Python language

used with Jupyter Notebook, Tensor Flow, and Keras. loss curve and accuracy curve of experimental data were generated using the Matplot tool to investigate the convergence of convolutional neural networks.

3- Classify vehicle

The following is a suggested research approach to classify mechanisms after conducting detection process show in (fig.4).

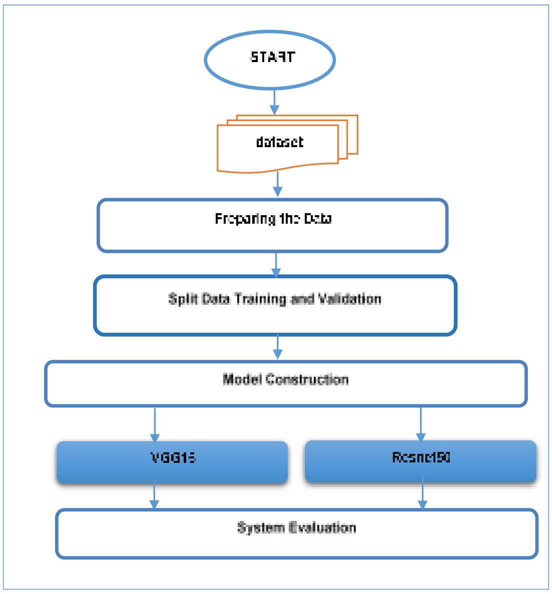

Fig.4. Methodology of Study

4- Hyper parameters

Several hyper parameters are used in setup of the training model, and they are applied to all models. Each model is trained using these hyper parameters, with the best results being retained for comparison and study of each model's performance in the future, such as (epochs: 80, Learning rate (α): 0.00001, Optimizer: Adam, patch size is 32).

5- Training models

2- Models of pre-trained Convolutional Neural Networks (CNNs) with Feature Extraction the ImageNet dataset is used to import the weights for pre-trained models like VGG16 and Resnet50. The models then trained using two image recognition categories on (8310) photos of ambulances and Trucks. Input size is (224 x 224 x 3) for the image, VGG16 final feature map is (512 x 7 x 7), and each model's summary is supplied for inspecting layers and feature maps in order to obtain high resolution. When the learning rate is 0.000001, the optimum model parameters for the model are obtained by stacking two densely linked classifiers, the batch size is (32), there are (80) epochs, and there are (207) steps each epoch. The feature map is used as an input to a full communication layer to obtain classification results. Although these pre_trained model beat the basic convolutional neural network, they do not minimize overfitting. As a result, these models necessitate the enhancement of image data and the fine-tuning of parameters. The accuracy of both training and validation curve of Resnet50 is shown in (Fig. 5). It can be observed that the training model's accuracy starts at around (97.68) percent and increases with each epoch as the model is trained. The level of loss at the conclusion of the period. The suggested model yields a high classification rate and a low loss rate, as can be observed.

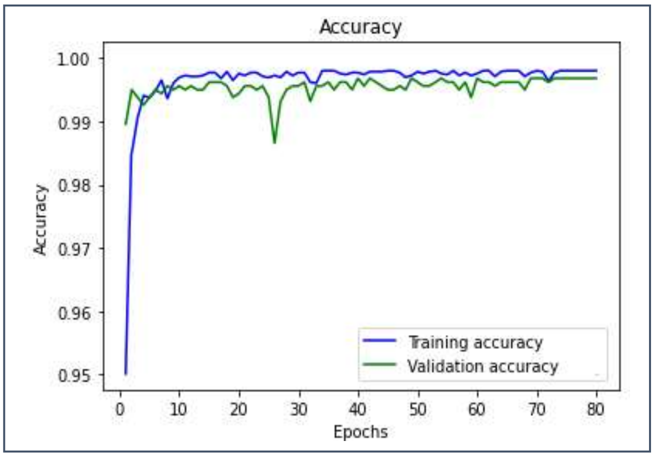

Fig.5.depicts the Resnet50 accuracy and validation curves.

Accuracy curve shows the VGG16 in (fig.6), where the accuracy increases with the start of training and the curve begins to rise with each age until it reaches a steady state. This network achieved a high classification accuracy of (99.87%) compared to Resnet50 network with a rapid decrease in the loss rate.

Fig.6. shows the accuracy curve and validation curve for depicts the VGG16 accuracy and validation curves

Fig.7 Pictures of system showing work of detecting ambulances and cars located within the ROI areas.

With picture size used 224 *224, we performed tests with several models to assess the accuracy of two types of convolutional neural networks, and the results shows are in table 1.

Models	Training Accuracy	Epochs no.	Dropout	Time(hour)
VGG16	99.87 %	80	0.1	58.30
Resnet50	97.68 %	80	0.1	41.26

Table 1. comparison between two models

Experimented with a number of hyper settings. As indicated in the table below, various accuracy was acquired for the VGG16 convolutional neural network using different organizing approaches, with the greatest accuracy found at dropout = 0.1 shows in the table 2.

Model	optimization	Dropout	Image size	Acc. %
VGG16	Adam	0.1	224*224	99.87
		0.1	64*64	98.94
		0.3	224*224	98.71
		0.3	64*64	97.28

Table 2. Effect of dropout and image size on VGG16 accuracy

Conclusion

In this paper, a model for allocating a smart road to emergency vehicles (ambulances) has been presented, where the system classifies cars on the road and divides them into two categories (ambulances and trucks) based on CCTV cameras, and since the ambulance suffers from road problems that hinder its access to the hospital or accident location, this model will address that issue and give precedence in this way to pass the emergency.

In such circumstances, no human effort would be necessary due to this automated procedure. The system achieved remarkable results in identifying emergency vehicles.

Deep learning models were used to address the difficulties of the ambulance and to discover the type of vehicle in the proposed system. This paper used Convolutional Neural Networks (CNN) (ResNet50 and VGG16), VGG16 networks were found to be the most effective in determining vehicle type in terms of speed, accuracy and size, and more work will be necessary to produce a new dataset of larger size and the same number of images for each vehicle type, as a result the network algorithm (VGG16) achieved an accuracy of vehicle classification up to (99.87%) and we got results in training the network algorithm (Resnet50) achieved an accuracy up to (97.68%).

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REFERENCES

[1] D. Sarpal, Y. Asthana, M. K. Hota, Review on Smart Traffic Management System for Ambulance, International Journal of Electrical Engineering and Technology(IRJET),11 (2020), No.6,1-9.

[2] A. Louati , S. Elkosantini , S. Darmoul and H. Louati, Multi-agent preemptive longest queue first system to manage the crossing of emergency vehicles at interrupted intersections, European Transport Research Review,(2018) No.10, 1–21.

[3] Kumar Chellapilla; Sid Puri; Patrice Simard, High Performance Convolutional Neural Networks for Document Processing, In Lorette, Guy (ed.), Tenth International Workshop on Frontiers in Handwriting Recognition, (2006).

[4] M. JUNAID, M. GHAFOOR, A. HASSAN, G. AHMED, T.ZIA, Multi-Feature View-Based Shallow Convolutional Neural Network for Road Segmentation, IEEE, 8(2020),36612 – 36623.

[5] V. Parthasarathi , M. Surya, B. Akshay, K. Murali Siva, Smart Control of Traffic Signal System using Image Processing, Indian Journal of Science and Technology,8(2015),No.16,1-5.

[6] K. Nellore , G.P. Hancke, Traffic Management for Emergency Vehicle Priority Based on Visual Sensing Sensors, 16(2016),No.11,1892.

[7] VAN-THUAN TRAN, WEI-HO TSAI, Acoustic-Based Emergency Vehicle Detection Using Convolutional Neural Networks, IEEE Access,8(2020), 75702 – 75713.

[8] Kaushik S ,Abhishek Raman, K.V.S Rajeswara Rao, Leveraging Computer Vision for Emergency Vehicle Detection-Implementation and Analysis, IEEE,(2020),1-6.

[9] M.A. H. Mansor; N. A. M. Kamal; M. H. Baharom; M. A. Zainol, Emergency Vehicle Type Classification using Convolutional Neural Network, IEEE International Conference on Automatic Control & Intelligent Systems (I2CACIS),(2021).

[10] Zhi-Hao Chen, Jyh-Ching Juang, YOLOv4 Object Detection Model for Nondestructive Radiographic Testing in Aviation Maintenance Tasks, AIAA JOURNAL, 60(2022), No.1,526-531.

[11] Wang, C., Liao, H.M., Yeh, I., Wu, Y., Chen, P., and Hsieh, A New Backbone that can Enhance Learning Capability of CNN, ArXiv: abs, (2019),1911-1192.

[12] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, Spatial pyramid pooling in deep convolutional networks for visual recognition, IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), (2015), 1904–1916.

[13] P. Mahto, P. Garg, P. Seth, J Panda, REFINING YOLOV4 FOR VEHICLE DETECTION, International Journal of Advanced Research in Engineering and Technology (IJARET), 11(2020), No.5, 409-419.

[14] Li. Mingchen, Car Image Classification Using Deep Neural Networks, Honors Theses, (2019).

[15] M. A. H. Abas, N. Ismail, A. I. M. Yassin, M. N. Taib, VGG16 for Plant Image Classification with Transfer Learning and Data Augmentation, International Journal of Engineering & technology, 7(2018), No.4.11,90-94.

[16] Srikanth Tammina, transfer learning using VGG-16 with Deep Convolutional Neural Network for Classifying Images, International Journal of Scientific and Research Publications, 9(2019), No.10.

[17] V. Sowmya, R.Radha, Efficiency-Optimized Approach - Vehicle Classification Features Transfer Learning and Data Augmentation Utilizing Deep Convolutional Neural Networks, International Journal of Applied Engineering Research ISSN, 15(2020), No. 4,372-376.

[18] Bin Li a, Dimas Lima, Facial expression recognition via ResNet-50, International Journal of Cognitive Computing in Engineering, 2(2021), 57-64.

[19] Poonam Dhankhar, ResNet-50 and VGG-16 for recognizing Facial Emotions, International Journal of Innovations in Engineering and Technology (IJIET),13(2019), No.4, 2319-1058.

[20] S. T. Krishna, H. K. Kalluri, Deep learning and transfer learning approaches for image classification, International Journal of Recent Technology and Engineering (IJRTE),7(2019), No.5S4, 427-432.