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Emergency vehicles classification for traffic signal system using optimized transfer DenseNet201 model

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ABSTRACT

As a result of the rapid growth of the world population, traffic signaling systems for monitoring and controlling the roads have turned to be an important issue facing humanity. To effectively overcome this problem, an accurate method for congestion reduction on the roads should be used which has a direct relation between the population and the cars' usage. Various approaches derived from deep and transfer learning have been investigated in this context. This research implemented an optimized transfer learning approach for densely connected convolutional neural network (DenseNet201) models for multiple classifications (non-emergency cars, ambulance, police, and firefighter). Due to the non-availability of public datasets, a customized dataset has been created. This paper aims to improve the performance accuracy of vehicle classification using certain preprocessing algorithms on the input images and testing various optimization methods. The performance accuracy of the proposed model is evaluated using k-folds cross-validation 20:80 for the test and training, respectively. The metrics which are used for comparison with other deep learning techniques are based on exactness, recall, accuracy and F1-score. Test outcomes specify that the proposed transfer model-based optimization outperforms alternative deep learning algorithms regarding vehicle accuracy in classifying and reaches 98.6%.

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1. INTRODUCTION

One of the major problems for urban traffic control is managing and reducing road traffic congestion. Nowadays, the number of vehicles in the traffic signal system is increasing, which causes a degradation of traffic road conditions. As a consequence of this increase, vehicles may face deadlocks and long queues at traffic intersections. This can lead to a loss of effective time, particularly in rush hours. In addition, urban traffic congestion also has potential impacts on the environment, health, and the economy state [1]. The main goal of setting the signal time management is to control the movement of people through an intersection in a safe and efficient manner. Attaining this aim needs a convenience plan for those who assign the right-of-way. Various parameters of traffic signal timing affect the performance of the road intersection including interval changes, cycle length, and green time. Consequently, the regulation of these parameters economically and efficiently reduces road traffic congestion and improves the traffic flow in urban streets [2].

Emergency vehicles often play a crucial role in many life-threatening situations. Traffic jam carries more than 20% patient's lives in an ambulance. However, when the patient's condition is critical, the death rate is increased. Most densely populated countries face excessive traffic blocking during the rush hours. Frequently, emergency vehicles such as (police, ambulance, and firefighters) get stuck in the traffic conditions which cause threatening-life in several situations. Therefore, it is essential to assign priority to these emergency cars and empty their paths by proposing an automated traffic system which will be able to detect them on congestion roads [3]. Moreover, accurate vehicle detection systems are required to classify them as emergency or regular cars. Deep and transfer learning techniques based on convolutional neural network (CNN) have been used in computer vision and they have made results not only comparable to humans but also higher than a human expert.

The deep convolutional neural network is one of the best techniques for detection and classification of objects in image and video. The CNN usually utilizes the approach of kernel filtering to process the image and the kernel's values are learned during the training phase. A deep CNN, which is constructed of stacking many layers, it has two limitations; it is difficult to train such network and it requires huge data to train it [4]. To overcome these kinds of shortcomings, transfer learning models can be used [5]. The general concept is to use knowledge learned from the pre-trained neural network model applied to different but related problems. various pre-trained models include AlexNet, visual geometry group (VGG)-19, ResNet-101, inception-v3, and densely connected convolutional neural network (DenseNet201) [6], [7]. Furthermore, image preprocessing algorithms and data augmentation have been widely used before feeding the input dataset to the trainer models because the datasets might be imbalanced and the quality of the images is noisy [8], [9]. Most recent advances and developments for deep learning applications in many fields have been presented, such as computer vision, medical image natural language processing (NLP), speech processing, and traffic congestion [10]. In traffic flow prediction, an intensive systematic review has been performed to find the gap and the best techniques of deep learning, which give a higher accuracy rate [11]. While in medical applications, DenseNet201 has applied for multiple sclerosis classification and COVID-19 infected patients [12], [13]. The latest development of NLP has contributed to significant implementation of speech recognition, machine translation, linguistic models, and automatic text generation using various deep learning architectures [14].

The importance of optimization algorithms for deep learning techniques must be taken into consideration for further improving the efficiency and accuracy of classification. It is considered as a critical part of deep learning for various reasons. First, it is tractable regardless of the non-convexity property and the second one is that the classical optimization algorithms cannot explain many phenomena. Accordingly, different optimizer methods including developed in deep learning include stochastic gradient descent (SGD) and adaptive gradient methods, Adam, Adamax, Adagrad, follow the regularized leader (FTRL) [15], and existing theoretical results [16], [17].

The main challenge of the intersection traffic signal control (TSC) problem is to determine an optimal configuration of traffic signaling system that allows a maximum traffic flow in a network. Besides, the traffic systems in developing countries like Iraq and Kurdistan Region of Iraq (KRG) are not reliable due to the numerous factors. First of all, the urban roads plan in busy cities is not organized according to international standards. Also, there is no standard dataset that contains emergency vehicle information, which leads to creating a customized dataset based on local vehicles' information. In this regard, an accurate system for traffic congestion reduction is required to build, which is the main goal of this study.

Researchers mostly use CNN and recurrent neural network (RNN) deep learning architecture for vehicle detection and classification. However, in this study, a transfer based deep learning system using DenseNet201was used as a main contribution to this work. The significant key contributions of the proposed model are as follows:

- Testing varying dimensions of input images (64*64, 128*128, and 224*224) to select the optimal image size for the training phase.
- Apply data augmentation to make the datasets balanced among emergency vehicles' types (police, ambulance, and firefighters).
- Modify some layers in DenseNet-201 to improve performance accuracy.
- Testing other deep learning models such as (MobileNet, VGG-19, and ResNet-101) on the same datasets to produce a fair comparison.
- Choose the best optimizer that increases the detection accuracy of the model.

In this paper, an improvement for classification in terms of performance precision is suggested for identification the emergency and non-emergency cars by using an optimized DenseNet201 model. It is based on customized image dataset as the input for training and testing processes. At first, all images are resized and then, processing through histogram equalization is performed. Furthermore, enhanced images are augmented to obtain balanced datasets for every class. Then the DenseNet201model for the purposes of training and testing is used. In the last step, the suggested model is assessed. for emergency vehicle detection using several optimizer algorithms. The structure of the remaining paper follows this sequence. In section 2, a survey about related works is investigated. While in section 3, methodology that includes dataset creation, data preprocessing, data augmentation, and DenseNet201 architecture for classification algorithms are described. Results and discussion are shown in section 4. Finally, the conclusions and recommendations for the future are unveiled in section 5.

2. RELATED WORKS

Various research works has been conducted by researchers to improve the accuracy of detection for emergency vehicles. Their main focus revolves around giving priority to models that are built upon deep learning approaches. Few studies have used transfer learning for traffic signal systems and traffic congestion. They mostly rely on the pre-processing algorithms for their improvements and tuning hyper-parameters of their proposed models.

Kumaran *et al.* [18] introduced intelligent TSC utilizing computer vision algorithms. They also proposed a novel approach based on traffic flow signal timing by optical flow features' clustering of moving vehicles using the temporal unknown incremental clustering (TUIC) model. Test results indicate that the proposed approach achieves better waiting time and throughput compared to other signal timing algorithms. Jing *et al.* [19] performed a systematic review of adaptive TSC in a congested vehicle environment. The system has an effective ability to reduce urban traffic congestion (i.e., delay minimization). The performance evaluation was formed based on previous research work to compare the advantages or disadvantages of those methods. Furthermore, a systematic framework of adaptive TSC based on connected vehicles is summarized to help future research. Other research directions are required to develop more generic adaptive TSC methods in a connected vehicle environment.

In real-time wireless network simulation, Faraj and Boskany [20] proposed an intelligent microcontroller circuit-based system which is efficient and cost effective for controlling cars in traffic congestion. The system can manage and control the traffic smarter than traditional traffic signal systems. It is also capable of adjusting the timing of traffic light signals dynamically and rapidly responding to road traffic, especially in rush hours, in order to decrease traffic congestion. They have used for the implementation; a server, cameras, microcontroller board as hardware components and wireless network infrastructure between traffic lights. Experimental results reveal that the system get higher accuracy when you only look once (YOLO)v3 as a machine learning tool and OpenCV as a preprocessing algorithm are applied. It can also minimize over 55% of the average waiting time in traffic intersections. An efficient reinforcement learning technique for traffic management system has introduced by Joo *et al.* [21]. They addressed the problem of traffic congestion by using an effective TSC method which is adaptive to increase the number of cars crossing an intersection and balance the signals between roads by using Q-learning (QL). According to their findings, the proposed method shows better performance compared to other research using QL in terms of waiting time and standard deviation of shortest queue lengths.

Sharma *et al.* [22] presented an intelligent framework for traffic light control systems using deep learning techniques. It uses YOLO deep learning model to detect objects coming from a video stream and simple online and real-time tracking algorithm (SORT) to track them over consecutive frames. They are emphasizing on Indian roads where the traffic conditions are critical. The proposed system has been tested on live traffic roads and it has been found to have a satisfactory result. In addition, they remarkably improved the traffic challenges at a very low cost by increasing and decreasing the timer based on road conditions. Occasionally, in a busy traffic zone, congestion patterns on multiple connected roads can make a complete jam of the network zone. To address this issue, Sun *et al.* [23] recommended a prediction model of congestion pattern in a heavily congested traffic area using the hidden markov model (HMM). The model initiates a connection between the external (observation state) and internal (hidden state) road traffic state of a busy traffic zone. To predict the zone of congestion pattern, HMM was adjusted by cleaning and mining of floating vehicle trajectory data. According to experimental results, the predictive precision may attain 83.4%, which is 5.8% higher than that moving average using the self-regressive model. This scenario outcome indicates the effectiveness and viability of the method for predicting congestion patterns.

Raji *et al.* [24] have introduced a novel approach to managing emergency states, particularly within congested traffic conditions. Addressing the challenge of impeded emergency vehicle passage during peak hours, the system effectively resolves temporal inefficiencies and traffic congestion. Whenever an emergency vehicle navigates a specific lane, an radio frequency identification (RFID) transmitter captures and transmits signal data, enabling an RFID receiver to facilitate a shift in traffic signal color from red to green, thus clearing the designated lane. Adaptation to traffic density prompts dynamic time interval adjustments of 10 or 6 seconds, yielding reduced congestion and travel time, thereby potentially preserving lives. The proposed system exhibits the ability to repeatedly ascertain vehicular density and grant automatic priority to emergency vehicles, utilizing

RFID technology for efficient motion detection and recognition. Conventional and deep neural networks commonly facilitate classification of both regular and emergency vehicles. In this respect, Mansor *et al.* [25] presented a classification method for emergency vehicles that are mainly found stuck in traffic congestion zones. Detection of emergency vehicles on the urban roads can provide a route to make emergency vehicles able to arrive on time more efficiently. They employed the VGG-16 model as the pre-trained model, modifying the convolutional layer and filter size to improve their result. According to the experiment, the proposed approach achieved an accuracy of 95%. While in, Haque *et al.* [4] developed and implemented an automated model for emergency vehicle detection based on emergency (ambulance and fire trucks) and non-emergency (other vehicles). YOLOv4 is first used for object detection using the region of interest (RoI) strategy and then the detected objects are trained using CNN and VGG-16 by fine tuning of model parameters. The average accuracy of 82.03% was obtained when the emergency vehicle identification v1 dataset is used. Ke *et al.* [26] have demonstrated an innovative technique for discerning road congestion within intelligent transportation systems, leveraging multidimensional visual attributes and CNN. The approach initiates by detecting foreground object density via a gray-level co-occurrence matrix. Subsequently, the Lucas-Kanade optical flow with a pyramid scheme is employed for the assessment of moving object velocity. Further stages encompass the application of a gaussian mixture model for background modeling, culminating in CNN-based precise identification of the ultimate foreground amidst prospective foreground candidates. The proposed method's efficacy is substantiated through comprehensive quantitative and qualitative evaluations, showcasing noteworthy superiority over prevailing road-traffic congestion detection methodologies, attributed to the integration of multidimensional attributes through CNN.

Some other researchers have conducted researches of using optimization algorithms in deep learning models. Alhudhaif *et al.* [27] adapted a combined version of a pre-trained CNN GoogleNet and particle swarm optimization (PSO), a nature-inspired optimization algorithm, for the classification of autonomous vehicles. The model was trained using a Kaggle dataset comprising vehicle images, augmented with various transformations. The trained model underwent classification through diverse classifiers, wherein the cubic support vector machine (CSVM) emerged as the most proficient, displaying superior performance in both time efficiency and accuracy (94.8%). Empirical and statistical assessments conclusively establish the model’s surpassing of comparable approaches not only in accuracy (94.8%) but also in training duration (82.7 s) and speed forecasting (380 obs/sec).

As stated by the aforementioned survey, an accurate result may not be achieved by using various types of traditional deep machine learning techniques. Therefore, to fill this gap in the research, an optimized transfer learning model with a higher accuracy based on DenseNet-201 is proposed. Also, a dataset for classification vehicle types has been developed.

3. PROPOSED METHODS

In object classification, significant findings can be effectively achieved using transfer learning, especially with limited dataset size. In addition, for further improvement of results, hyper-tuning of deep transfer learning DenseNet201-based model can be used. This mode, which is reused a pre-trained model can relatively use complex model to reduce the amount data by transferring the learnt knowledge to smaller amount of data as illustrated in Figure 1. In this paper, the methodologies that have been used consist of numerous processes as shown in Figure 2. The general block diagram contains the subsequent stages:

- Data compilation: vehicles gathering images from available public dataset and local traffic offices in KRG- Iraq.
- Image labeling: vehicles image annotation based on emergency (ambulance, police, and firefighter) and non-emergency cars. Therefore, four types of vehicles are prepared before being fed into the model training.
- Improvement of image quality: employ preprocessing algorithms include image resize, image sharpening, image smoothing, and contrast enhancement.
- Data augmentation: using different image transformations to overcome the overfitting problem and make the datasets balanced.
- Dataset partitioning: for cross-validation, 80% of the data was allocated to training, while 20% was reserved for testing and validation.
- Proposed transfer model training: assemble it with tuning some parameters.
- Vehicles categorization: the emergency and non-emergency vehicles types are based on multi-classification.
- Performance metrics’ evaluation: loss-accuracy curve, confusion matrix, precision, recall, F1-score, and average accuracy.

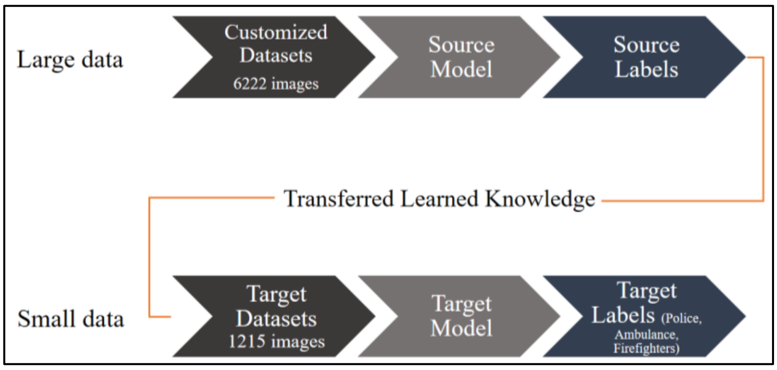

Figure 1. Transfer knowledge learning-based processes

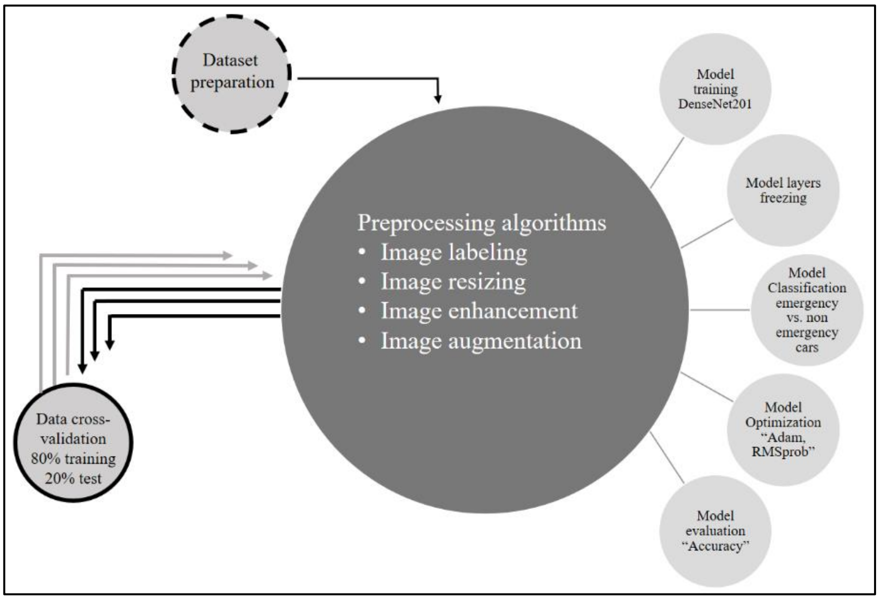

Figure 2. General diagram of proposed model

3.1. Dataset preparation

This study relied on emergency and non-emergency vehicle images as a dataset. Due to the non-availability of an open dataset which includes emergency cars (police, ambulance, firefighters), a customized dataset has been created. The vehicle images used in this work were collected from different sources (Kaggle, Fatkun Batch, and Rania traffic directorate in Kurdistan reign–Iraq). Nevertheless, the vehicle images exhibit variations in size and unbalanced in class types. Dataset for emergency and non-emergency vehicle is presented in Table 1.

Table 1. Unbalanced datasets

Vehicle types	Total number	Training (80%)	Test (20%)
Ambulance	322	257	65
Firefighters	526	422	104
Police car	700	560	140
Non-emergency	1,670	1,336	334

3.2. Algorithms for data preprocessing

Image preprocessing algorithms can be considered a range of techniques that involve applying specific operations to an image in order to enhance its quality. The initial steps encompass the resizing of images to various dimensions (6,464, 128,128, 224*224) in accordance with model prerequisites. These images are subsequently categorized into emergency and non-emergency vehicle classes. Often, image quality is compromised due to factors such as electronic device effects and lighting conditions. Consequently, the implementation of preprocessing algorithms assumes a pivotal role in preparing the images for the classification process. This study underscores the vital importance of image sharpening, image smoothing, and contrast enhancement in refining image quality, thereby offering valuable support to downstream tasks like image segmentation, detection, and classification. Besides, data augmentation has also been applied to make datasets balanced and to overcome the problem of overfitting among classes. Table 2, presents a balanced dataset for both emergency and non-emergency vehicles.

Table 2. Balanced datasets

Vehicle types	Total number	Training (80%)	Test (20%)
Ambulance	1,610	1,285	325
Firefighters	1,682	1,266	416
Police car	1,260	1,120	140
Non-emergency	1,670	1,336	334

3.3. Model structures

The proposed model uses the "DenseNet201" for feature extraction and CNN for the classification. The design and implementation of the proposed approach comprises three steps: apart of preprocessing, feature extraction, classification, and optimization are presented. Figure 3 shows the stages of the proposed model architectures.

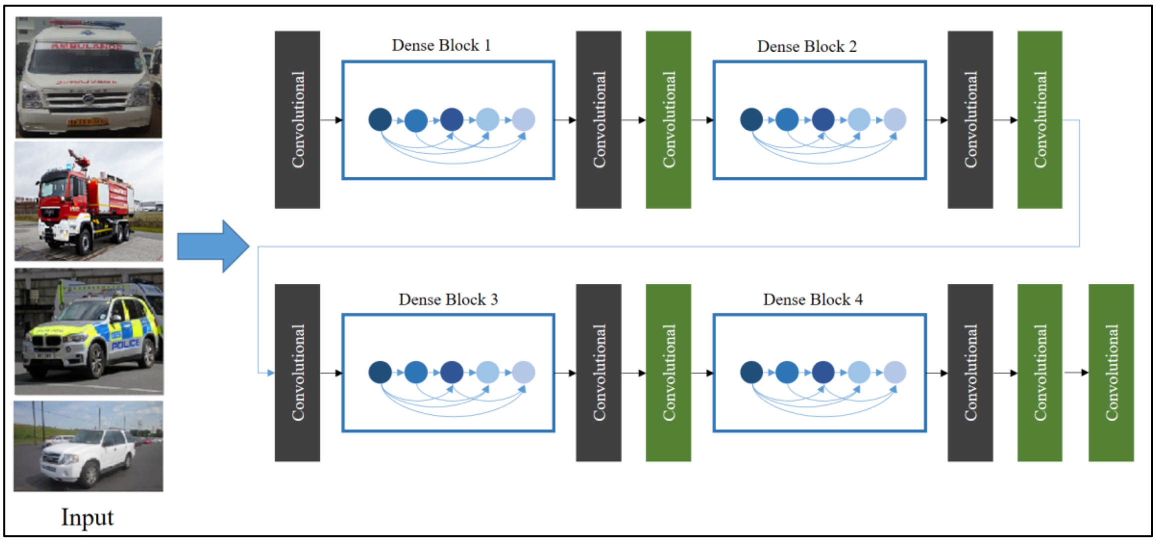

Figure 3. DenseNet201 with CNN for classification

3.3.1. DenseNet architecture

The evolution of DenseNet201 proposes the remarkable potential of the dense architectural framework to achieve cutting-edge outcomes. This advancement is particularly evident in scenarios where a modest growth rate is adopted, resulting in the perception of feature maps as a comprehensive network-wide resource. As a result, each sequential layer enjoys unfettered access to the entirety of feature maps stemming from preceding layers. The incremental contribution of K feature maps to the global network state transpires within each layer, defining the cumulative input feature maps at the l^{th} layer as:

$$(FM)^l = K^0 + K(l-1) \tag{1}$$

here, K^0 signifies the input layer's channels. The enhancement of computational efficiency is portrayed in Figure 4, where in a (1*1) convolutional layer precedes each (3*3) convolutional layer, thereby curtailing the volume of input feature maps. Serving as a bottleneck layer, the (1*1) convolutional layer engenders the production of 4K feature maps. For classification purposes, the incorporation of two dense layers housing 128 and 64 neurons, respectively, is realized. The modified feature extraction network, encompassing a truncated DenseNet201 architecture, is augmented by a sigmoid activation function for binary classification, thereby supplanting the conventional softmax activation function employed within the established DenseNet201 framework as depicted in Figure 4. The sigmoid function's definition is as:

$$y = \frac{1}{1+e^{-(\sum_i wi*xi)}} \tag{2}$$

where y is the output of the neuron. wi and xi represent the weights and inputs, respectively.

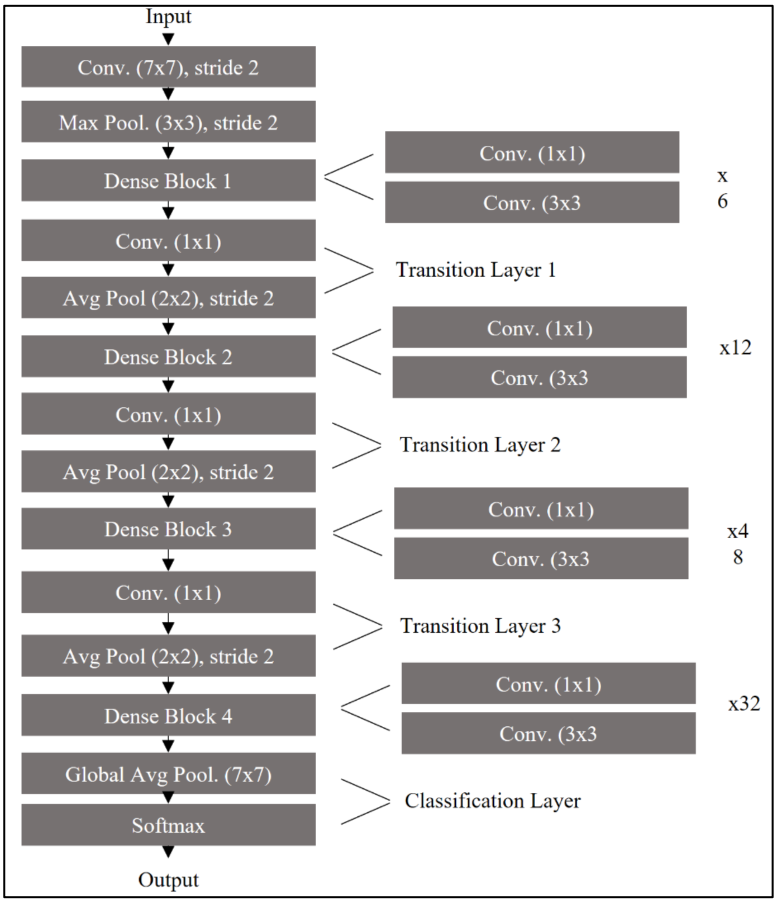

Figure 4. DenseNet201 architecture

3.3.2. Freezing DenseNet201 layers

Concerning neural networks, the concept of freezing layers pertains to regulating the manner in which weight updates transpire. A frozen layer signifies that the associated weights remain unaltered during subsequent processing. This strategy, though seemingly straightforward, operates to curtail computational expenditure during training, while concurrently incurring a negligible compromise in detection accuracy. Thus, layer freezing constitutes a strategic tactic to expedite neural network training through the gradual immobilization of concealed layers. In this paper, several freezing layers are performed on DenseNet201 layers in order to show its impact on performance accuracy.

3.3.3. Optimizer algorithms

Various optimization methods that have existed in literature have been widely used in recent research related to deep transfer learning. They are used to reduce the loss function and update the weights in back-propagation. Gradient descent can be used to compute the local minima of numerous functions. The gradient is determined by evaluating the loss function for the entire dataset. The SGD has drastically reduced the amount of computation needed by considering only one data point at a time. The mathematical formula used by all the optimizers for updating the weights and with certain learning rate values is as:

$$w_x' = w_x - \propto \left(\frac{\partial error}{\partial w_x}\right) \tag{3}$$

where w_x' denotes the updated weights while w_x represents the old weights and $\propto$ indicates the learning rate. $\left(\frac{\partial \mathrm{error}}{\partial \mathrm{w_x}}\right)$ is a derivative of error with respect to weights. Different algorithms implement adjustable learning rates. As an illustration, the AdaGrad optimization method entails the personalized adjustment of learning rates for individual parameters, predicated on the cumulative sum of historical gradient squares. This approach inherently incorporates a learning rate decay owing to the accrual of gradients, a phenomenon that can potentially halt the optimization process. To circumvent this, the root mean square propagation (RMSProp) technique introduces the notion of a moving average of squared historical gradients, incorporating exponentially diminishing weights. In the domain of deep learning, the Adam optimization algorithm and its derivative forms are extensively prevalent. Adam embraces the concept of exponentially decaying moving averages for both past gradients and their corresponding squares. In this paper, the effect of each optimizer on the accuracy rate is investigated by transferring deep learning DenseNet201 with and without freezing layers. Model accuracy is shown in the Figure 5.

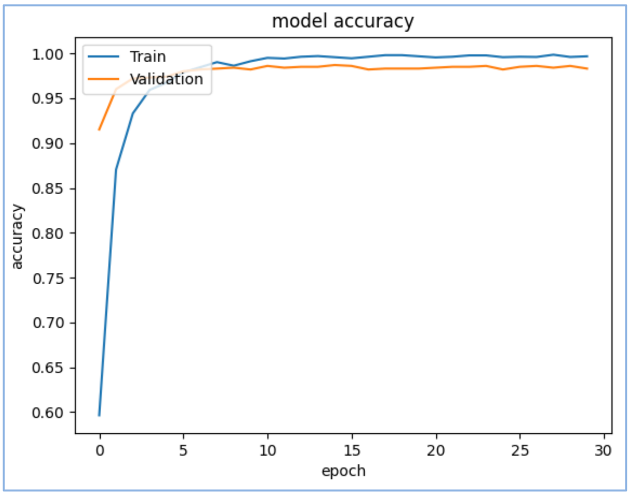

Figure 5. Model accuracy

4. PERFORMANCE RESULTS AND EVALUATION

The proposed model is compiled and trained with the above-estimated training data over the range of 0-30 epochs or iterations. Performance parameters such as accuracy, precision, recall, and F1 scores are utilized for the estimation of model efficiency and performance accuracy. The following equations define these parameters consecutively [28];

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

$$\text{Precision}=\frac{TP}{TP+FP} \tag{5}$$

$$\text{Recall}=\frac{TP}{TP+FN} \tag{6}$$

$$\text{F1}=\frac{2\ x\ Recall\ x\ Precision}{Recall+\ Precision} \tag{7}$$

where true positive, true negative, false positive, and false negative are denoted by true positif (TP), true negative (TN), false positif (FP), and false negative (FN) respectively.

4.1. DenseNet201 based loss and accuracy functions

The DenseNet201 model successfully optimized. After that to recognize normal and emergency vehicles with better accuracy and validation, we have plotted the model accuracy graph containing training and validation accuracy. Finally, the model loss graph plotted which is containing training and validation loss and depicted in Figure 6.

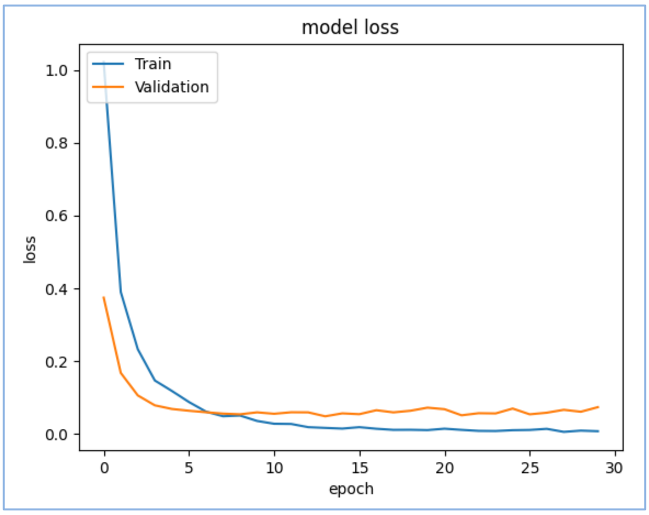

Figure 6. Accuracy and loss in the model training and validation

Furthermore, the confusion matrix (CM) of the proposed vehicles classification model is plotted. The CM is demonstrated in Figure 7. The diagonal of the plotted confusion matrix represents the proposed model performance accuracy for different types of emergency cars.

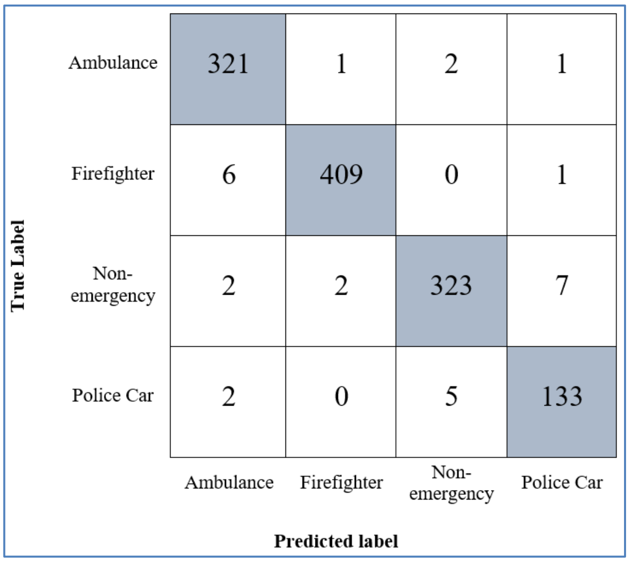

Figure 7. Confusion matrix for the model performance evaluation

The recent deep learning techniques of evaluation have been used to evaluated the presented model. Table 3 presents the evaluated value of the exactness, recall, and F1 score for every individual emergency and non-emergency vehicles type. CM in Figure 6 was used and the optimal optimizer RMSProp has used with the proposed DenseNet201 model.

Table 3. Model performance evaluation

Vehicle types	Precision (%)	Recall (%)	F1 (%)	Avg. accuracy (%)
Ambulance	98.18	97.01	97.59	98.44
Firefighters	98.48	99.69	99.08	
Police car	99.76	99.76	99.76	
Non-emergency	95	95	95	

4.2. Data augmentation effect on performance accuracy

As presented in Tables 1 and 2, the problem of imbalanced data was solved by performing data augmentation on the input images through various transformations such as (vertical flip, horizontal flip, sharpening, and brightness contrast) for emergency vehicles class. Various experiments were conducted for different image sizes, epoch's numbers, deep techniques, and optimizer algorithms. Here, we only present the results of using layer's freezing in DenseNet201 for both imbalanced and balanced datasets. Image size of 224*224, epoch=15 and best optimizer Adam were chosen to show the effect of layer's freezing with optimized DenseNet201 on the performance accuracy. Figure 8 illustrates the average accuracy rate for the vehicles classification before and after data augmentation. As can be seen that with freezing of the first 30 layers of DenseNet201, the accuracy reaches 98.6% for balanced data while attains 96.64% for imbalanced data.

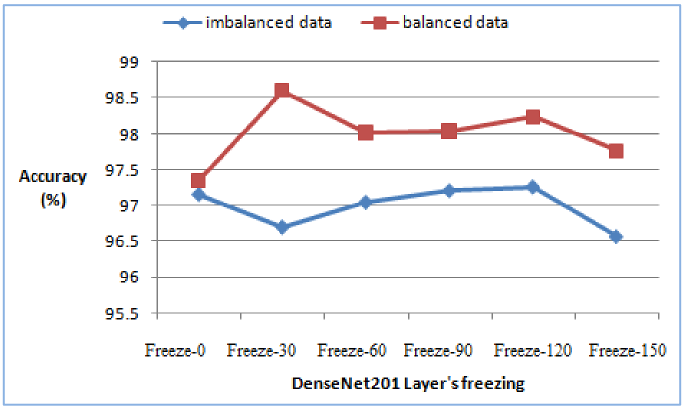

Figure 8. Accuracy detection with and without data augmentation

4.3. Model performance comparison

This work was done based on the use of the customized dataset collected from different sources. The best accuracy was obtained using preprocessing, data augmentation, and layer's freezing, optimal optimizer on the use of DenseNet201 architecture. In Table 4, some related studies are compared to the accuracy of the proposed model. It can be clearly seen that the proposed approach using optimized DenseNet201obtained an average accuracy of 98.4%, which outperforms other deep learning techniques.

Table 4. A comparison of the proposed model's accuracy with related previous studies

Reference	Methodology	Dataset	Test accuracy (%)
Haque *et al.* [4]	VGG16	Emergency vehicle identification v1	82.03
Jaiswal *et al.* [13]	DenseNet201 with CNN	SARS-CoV-2 CT scan (2,492 images)	96.25
Faraj and Boskany [20]	YOLO-v3	Customized (2,000 images)	95
Proposed models	DenseNet201 with CNN+RMSProb optimizer	Imbalanced data (3,218 images)	96.7
	DenseNet201 with CNN+RMSProb optimizer+30 layers freezing	Balanced data (6,222 images)	98.6

5. CONCLUSION

This paper introduces a revised deep transfer learning model tailored for vehicle detection emergency and non-emergency cars with the help of CNN and pre-trained DenseNet201 model. The proposed model can accurately classify the emergency vehicles using preprocessing, data augmentation, layer freezing, and best optimizer. The optimal accuracy achieved from the proposed model is 98.6%. 2% improvement has been achieved from the proposed model, when it was compared with other competitive models. The future work intends to use different k-fold cross validation (10:80 and 70:30) to validate the reliability of the model. Also, the model will test in a real-time environment to show the reduction of congestion in traffic signal system.

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