



Emergency Vehicle Detection in Heavy Traffic using Deep ConvNet2D and Computer Vision

Guntur Manisha, Gadupuri Sowmya, Ms.Pavithra Babu, B.E, M.E.

^aSathyabama institute of science and technology , Chennai 600119 , Tamil Nadu , India

Abstract: A surveillance system called smart detection of emergency vehicles can identify emergency vehicles that are stuck in traffic. This system is useful for better traffic management because of the increasing number of vehicles on the road over the past few years, which causes congestion. The emphasis of this project is on a method to implement emergency vehicle recognition using Deep ConvNet2D. We propose a model with a convolutional neural network (CNN) architecture for detecting emergency vehicles that makes use of real-time image processing. When an emergency vehicle is detected, the signal control unit can be programmed to preferentially end the round robin sequence. A CNN is trained on a dataset of Indian ambulance images to solve the problem that has been described. TensorFlow, a deep learning platform available as a Python library, was used for training. Our method has shown good result in detecting and classifying emergency cars. In the existing system, ANN algorithm is used and the accuracy and efficiency is very low. In the proposed system, Deep ConvNet2D Algorithm is implemented. The proposed system is implemented in real time and features high accuracy. When compared to the system that is currently in use, both the loading speed of the proposed system and the execution speed are extremely quick. In addition to being enhanced for more complex use cases, the proposed system is extremely scalable and efficient.

Keywords— Artificial Neural Network (ANN) algorithm, Deep ConvNet2D Algorithm, Convolutional Neural Network (CNN).

1. Introduction

Delay in EMS is the reason of India's high road accident death rate. From reporting an accident to summoning an ambulance to handing over the patient, every step is delayed. Delay reduction saves lives. We offer an accident detection and ambulance management system. The main server immediately sends the closest ambulance when the in-car accident detection module detects an accident. Every situation that even remotely threatens human life requires emergency vehicles. Over 20% of EMS patients die due to traffic jams. Life-threatening diseases increase the death rate of patients. An emergency patient must be delivered to the hospital as soon as possible, but the ambulance becomes delayed in a traffic bottleneck. This creates a problem if cardiac patients need to be moved quickly. When traffic is backed up, many people don't want to move over for emergency vehicles, and authorities don't know which lane to clear.

Many die before reaching hospital. Integrating an intelligent automated system with a traffic management system may help. Emergency vehicles will be prioritized. We must recognize emergency vehicles. They gave each automobile emergency or normal status after recognizing it. In an emergency, the computer may alert authorities or a road-clearing robot. Emergency vehicle response time is critical in a disaster. Success depends on its ability to navigate crowds and accomplish its objective quickly. These trucks formerly featured lights and sirens to attract pedestrians and drivers.

A video series of streets may be edited and analyzed so that cars can be counted and identified. Several approaches exist to achieve this. Using a computer vision system allows the calculation of supplementary data, including vehicle speed or traffic density. Two groups may gain immediately from this. Road users and traffic management organizations. Users who are aware of constant traffic data may pick the most efficient way to travel, avoiding congestion and saving time. Traffic-controlling organizations may use traffic data in system.

The paper's main contributions can be summarized as follows:

- To preserve the patient's life, we suggest developing a car detection model utilizing a deep learning algorithm
- This system has been enhanced for more complex use cases and is extremely scalable.

2. Literature Survey

Transportation is a major economic factor. Unorganized transportation harms most economic sectors. Developing nations encounter this difficulty. Highways should be created to enhance the transportation network's throughput; however, Sri Lanka's shrinking land space and growing population make road growth impossible. Thus, a more efficient, technologically sophisticated solution is needed. In addition to regular traffic jams, the pandemic crisis has prioritized ambulances. The road network also includes pedestrians. Effective pedestrian crossings reduce vehicle accidents and improve congested traffic. In this scenario, a smart traffic monitoring system that controls traffic lights is perfect. This study offers an adaptive traffic monitoring and control system that prioritizes emergency vehicles. New You Only Look Once, Version 3 (YOLOV3) trained Convolutional Neural Network (CNN) achieves 91.3% detection accuracy. High demand has boosted automobile manufacturing and sales. Due to increased automobile use, road accidents are worrying. Year-over-year, traffic accidents rise. Accident fatalities are rising. Road collision death rates are due to both driver safeguards and emergency service delays. Timely treatment saves many lives. Many factors delay wounded people's care. Delays in hospital communication and severe traffic might delay emergency vehicle service to the wounded. Utilizing the smart phone [1]- automated accident detection, and alert system, Internet of things (IoT) is suggested to identify accidents and notify neighboring hospitals. External pressure sensor detects vehicle body force. This document measures speed, accelerometer, and Global Positioning System (GPS) angle change [2].

It enhances safety. I/O Virtualization (IoV) provides computation, storage, and networking for vehicles. Unannounced events, construction, and

peak-hour traffic cause accidents. Non- line-of-sight vehicles transmit data. High-mobility Dynamic topology defines IoV networks. Control and data planes are separated with centralized Software-Defined Networking (SDN) . SDN improves traffic and vehicle communication. SD-IoV reduces broadcast storm traffic. Using selective forwarding and vehicle neighbor awareness, the suggested broadcast routing system reduces traffic bottlenecks and travel time. Accident-detecting On-Board Unit (OBU) transmits Software Defined – Input Output Virtualization (SD-IoV). Machine learning simulates 90% accurate OBU crashes. IoV simulations show SDN controller high packet delivery and low latency [3].

Building and assessing autonomous vehicle emergency braking algorithms reveals environmental factors. Quick calibration and detection may improve lane line recognition. In 'L' is the lightness, whereas 'A' (green / magenta) and 'B' (blue / yellow) (LAB) and U and V are color image chromaticity values, while L stands for luminance. (LUV) color spaces, yellow and white lane line figures are detected, and a quadratic curve model is produced to restore the lane geometry model and give a foundation for quick geometric vehicle placement when the Autonomous Emergency Braking (AEB) algorithm is developed. A convolutional neural network method is created to recognize and categorize ambient vehicle targets 87.1% training accuracy. The network was tested in South China. Accurate, real- time environmental feature identification [4].

Accidental deaths hurt economic progress. Most poor countries have more road fatalities due to a lack of a system to inform emergency responders quickly. Accident victims' life depends on how quickly Emergency Medical Technicians (EMTs) arrive and transfer them to the hospital. Traffic may slow emergency vehicles to and from an accident location. This research presents an automated automotive accident detection and the alarm model that uses a speedometer to identify turning and crashing and sends accident site's GPS location to security, medical, and family contacts. This gadget is faster than typical rescue methods. Tech saves lives [5].

Due to their medical emergency efficiency, traffic avoidance, journey duration, and fuel consumption, autonomous cars have grown exponentially in recent years. Lane level localization, a feature of selfdriving cars, is ripe for innovation. Its many benefits are offset by poor road structures, low nighttime visibility, road shadows, and vehicle intervention. Light Detection and Ranging (LiDAR), GPS, Inertial Measurement Unit (IMU), cameras, etc. have emerged in recent years to overcome these challenges. Growing demand for precise, affordable technologies. Visionbased solutions revolutionized lane detection, accident prevention, and installation costs. Traffic path detection is done

with Radio-Frequency (RF) sensors and a camera. because to its easy tracking and steering, a cloth aid road model is used to define a vehicle's motion path. Vision-based data evaluates fabric and traffic. RF sensors calculate vehicle location and speed. This approach is preferable due to low-cost sensor installation and accurate lane detection in heavy traffic [6].

Neural networks have helped advance computer vision applications like object identification. Such success depends on expensive processing resources, which prevents those with inexpensive equipment from appreciating modern technologies. This study says, we propose the term called Cross Stage Partial Network or also known as CSPNet to reduce and also need for network architecture-based inference calculations. We blame network optimization's redundant gradient information. The suggested networks respect gradient variability by combining feature maps from the beginning and end of a

network stage, which considerably outperforms state-of-the-art methods on the Microsoft Common Objects in Context (MS COCO) object detection dataset while reducing computations by 20% with similar or greater accuracy. It is easy to implement and can handle Residual Network (ResNet) , Residual Next (ResNeXt) , and Dense Network (DenseNet) architectures [7].

Other drivers must yield to Emergency Vehicles (EVs) with audible and visual warning signs. EVs might cause delays or crashes if drivers don't see them. This paper offers audio- and vision-based EV detection devices to inform drivers. First, we propose You Only Look Once – Emergency Vehicle Detection (YOLO-EVD) and a vision-based picture dataset. CSPC at YOLO-neck EVD's boost detection performance, attaining 95.5% mean average accuracy. Second, we propose Wave Residual Network (WaveResNet) for audio- based Emergency vehicle detection with a onesecond raw waveform input, WaveResNet achieves more than 97% accuracy in regular traffic. It is noise resistant. Realtime YOLO Emergency vehicle detection with WaveResNet. We merge YOLO-EVD with Using WaveResNet, an EVD system for AudioVisual content (AVEVD) has a 1.54% misdetection rate, according to our studies. An Emergency vehicle detection and AV Emergency vehicle detection are utilized for private vehicles, autonomous cars, and smart road infrastructure [8].

Deep learning (DL) is effective in medical imaging, and after the COVID-19 epidemic, researchers are investigating DL-based lung disease identification solutions. This paper analyses LUS images using DL, whereas existing research focuses on CT scans. We offer an annotated collection of LUS images from Italian hospitals, with labels indicating illness severity at a frame-, video-, and pixel- level. Using this data, we build autonomous LUS image analysis models. We introduce a Spatial Transformer Network-based deep network that predicts disease severity and localizes pathological artifacts. Uniform-based frame score aggregation is also available. Finally, we test deep models for COVID-19 biomarker segmentation. Experiments on the provided dataset show good results on all tasks, allowing further research on DL for aided COVID-19 diagnosis using LUS data [9].

Classification neural networks have been extensively utilized in computer vision to classify images with deep learning. Using the LeNet, VGGNet, RestNet, and Wide-ResNet models to classify Tibetan old writings and characters, this study compares and analyzes the experimental results.. According to experiments, the aforementioned neural network models are effective at classifying photos of Tibetan single-character fonts, with the Wide- ResNet model having the best results. (94%). This paper's experimental data helps classify Tibetan ancient books and images [10].

3. Existing System

The existing system are not done in real time and also the current system performs poorly in terms of loading speed and implementation speed. Additionally, The testing and training do not make use of the appropriate test-train split ratio.

Table 1 - Comparison Analysis of diverse Approaches

Title	Author	Year	Cons
Pros			
Acoustic-		2020	This can only

Based on Emergency Vehicle Detection Using Convolutional Neural Networks Adaptive fault

VanThuan Tran et al.

system that recognised by checks to see if sound of the vehicles there are sirens from emergency vehicles nearby to make an automatic detection and warn other drivers to pay attention.

Jong Min 2022 To guarantee the Detection

detection and emergency control of autonomous vehicle for fail safe system using sliding mode approach Road anomaly detection through deep learning approaches Development of Reinforcement learning based traffic predictive route guidance algorithm under uncertain traffic environment Emergency pull over algorithm for level 4 autonomous vehicle based on model free adaptive feedback control with sensitivity and learning approach

Lee et al.

functional safety of autonomous vehicles, a sliding mode control appropriate (SMC)-based emergency control method designed to respond to faults had been proposed. It is used to classify the vehicle. It is used to achieve shortest travel path to reach the required destination.

The model should be trained. It is an older traditional system which needs to be updated.

Dawei Luo et al. 2020

Donghoun Lee et al. 2022

An The estimated addition sensitivity and adaptation gain al distance are used to condition has update feedback been proposed in gain.. the GD method to reduce the number of tuning parameters needed.

4. Methodology

4.1. Data

Acquisition and Pre-Processing

Kyongsu Yi et al 2022

Data

Acquisition: The photos in the collection are noisy and of poor quality

because they were obtained from online sources. Data set is taken from Kaggle for the car.

Data Pre-processing: Making data more meaningful and informative is the effort of changing it from a given form to one that is considerably more useable and desired. This process can be automated using Machine Learning algorithms, mathematical modelling, and statistical expertise.

Removing Unwanted Parts of Images: An image may contain artifacts (irregularities) or unwanted regions that are not always desirable. Once such regions have been identified, it is necessary to identify their types in order to devise the best method for eliminating them. To begin, we imported the Numpy module and the PIL image library. This would enable us to store uniform pixel values in arrays, allowing for faster operations on them. **Removing Noisy Images.** We can remove noise from photos by using cv2.fastNIMeansDenoisingColored(). We define the following parameters h: the filter strength determining parameter.

4.2. Model Creation and Training

Model Creation: CNN comes under Machine Learning Algo, helps to extract different image which help in classifying images. The Convents has different layers discuss below.

Introduction to the network: A mathematical model called a neural network was created to roughly match the human brain. One of the various kinds of neural networks is the convolution neural network (CNN). CNN focuses on image processing and can be used for object identification, segmentation, and classification of images.

Pooling Layer: The Pooling layer reduces the spatial size of the Convolved Feature..Through reduction of dimensionalitythere will be less need for computing power to process the data..

Fully Connected Layer: It will use a convolution layer's output to teach non-linear features. This output should be transformed into a column vector for multi-perception and sent to a feed-forward neural network with back propagation during each training cycle.

Loading Data into Batch: Batch processing is the a method for consistently processing a large amount of data. When computational resources are available, users can process data with little or no human intervention using the batch technique.

4.3. Implementation

We import NumPy, matplotlib.pyplot. Importing cv2, re, and os. The collision xml file was then added. Save as.xml and use this video as input. cv2.CascadeClassifier() loads the learned model. We'll use detectMultiScale() to locate automobiles in video frames. The detectMultiScale() function returns coordinates using three parameters. Grayscale In this case, a grayscale image is fetched from video streams. ScaleFactor specifies how much image size is reduced at each image scale. This parameter affects the quality of the detected faces. A good value

is 1.05 min neighbors. Larger values result in fewer but higher-quality sightings; 3-6 is a good range. The code identifies cars in the frame image and returns their exact locations.

5. Analysis

This Analysis depicts the comparison of accuracy between CNN and ANN where CNN has better accuracy compared to ANN. So, it is better to use CNN. From the given Figure 1 we can clearly see that CNN has 90% accuracy compared to ANN. Similarly, if we observe ANN it has 84% accuracy and most beneficial network we suggest is CNN technique to implement vehicular detection.



Fig. 1. Comparison of Accuracy

6. Conclusion

We used Extreme Learning Machine (ELMs) to classify audio data. Mel-Frequency Cepstral Coefficients (MFCC) and Zero-Crossing Rate (ZCR) are raw data-based. SMOTE's consistency checks eliminated falsely high accuracy. ELM sped up analysis without sacrificing accuracy. ELMs reduced training time while achieving 97% accuracy. CNN, MLP, and KNN are 4,000 times slower than ELMs. These models are good for online machine learning, where they're constantly updated. A model can learn in real time with machine learning. Internet-based real-time machine learning. We haven't studied ZCR. Sound sensing might replace traffic cameras, radar, and loop detectors. These data may help us find unexpected events. Sliding tires require audio data, which may indicate aggressive driving. Cameras, radar, and loop detectors can't detect danger. Audio sources detect rain and storms.

Acknowledgements

We would like to appreciate the efforts of the reviewers of this paper and we extend our gratitude to the faculties of Sathyabama university.

REFERENCES

[1]Munasinghe, K. D. S. A., Waththegedara, T. D., Wickramasinghe, I. R., Herath, H. M. O. K. & Logeeshan, V., (2022). Smart Traffic Light Control System Based on Traffic Density and Emergency Vehicle Detection. Moratuwa Engineering Research Conference (MERCCon).

- [2]Devi, C. & Gowri, S., (2021). An Automatic Smart Phone with IoT based Accident detection and alerting System. 5th International Conference on Electronics, Communication and Aerospace Technology (ICECA).
- [3]Raja, G., Dhanasekaran, P., Anbalagan, S., Ganapathisubramanian, A. & Bashir, A. K., (2020). SDN-enabled Traffic Alert System for IoV in Smart Cities. IEEE INFOCOM - IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPs).
- [4]Zheng, J., Zheng, M., Chen, C. & Yu, M., (2020). Research on Environmental Feature Recognition Algorithm of Emergency Braking System for Autonomous Vehicles. 5th International Conference on Electromechanical Control Technology and Transportation (ICECTT).
- [5]Chikaka, P. & Longe, O. M., (2021). An Automatic Vehicle Accident Detection and Rescue System. IEEE 6th International Forum on Research and Technology for Society and Industry (RTSI).
- [6]Gupta, S., Pati, U. C., & Parameswari, D. C., (2022). Traffic Lane Localization using Clothoid Road Model. Second International Conference on Computer Science, Engineering and Applications (ICCSEA).
- [7]Wang, C. -Y., Mark Liao, H.-Y., Wu, Y. -H., Chen, P. -Y., Hsieh, J. -W., & Yeh, I. -H., (2020). CSPNet: A New Backbone that can Enhance Learning Capability of CNN. IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW).
- [8]Tran, V. -T., & Tsai, W. -H., (2021). Audio-Vision Emergency Vehicle Detection. IEEE Sensors Journal.
- [9]Zhao, Z., (2022). Research on single-character image classification of Tibetan ancient books based on deep learning. 3rd International Conference on Computer Vision, Image and Deep Learning & International Conference on Computer Engineering and Applications (CVIDL & ICCEA).
- [10] Roy et al., S., (2020). Deep Learning for Classification and Localization of COVID - 19 Markers in Point- of - Care Lung Ultrasound. IEEE Transactions on Medical Imaging.
- [11] Zheng, Z., Zhou, M., Chen, Y., Huo, M., & Sun, L., (2020). QDetect: Time series querying based road anomaly detection. IEEE Access, 8, 98974–98985.