Intelligent Sensors for the Detection of Outlawed Vehicles on Highways

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Abstract

Road accidents are on the rise, especially in countries like Pakistan. This often occurs when someone disregards or violates the law, resulting in the loss of precious lives and property. The roads are designed for rapid transportation, but not all vehicle types are permitted, requiring proper care when entering. In this research, we have explored using AlexNet to detect vehicles not allowed on the Pakistan Highway. A live sensor will monitor each vehicle as it enters the highway, and when a forbidden vehicle attempts to enter, the sensor will automatically alert the relevant authorities. Recent research has developed various strategies for categorizing and identifying vehicles using numerous machine learning techniques, particularly deep learning. Compared to other technologies, CNN and its variations have proven most effective in identifying vehicles in both still and moving images. We employed AlexNet and LeNet to identify outlawed/banned vehicles on highways using Deep Learning Techniques. The sensing system can be integrated with IoT mechanisms.

Keywords: *Machine Learning; Intelligent Sensors, Deep Learning; Road Security, CNN; AI-IoT.*

Introduction

Pakistan's highway network is owned and maintained by the Pakistan national highway authority, featuring multiple high-speed lanes. While 1883 km of the highway is operational, an additional 1854 km is under construction. Highway Police patrol these roads, using SUVs, cars, and heavy motorcycles.

The highway authority has regulations prohibiting certain vehicles from accessing the highway. These vehicles may be less secure, underpowered, or lacking adequate passenger protection. Additionally, vehicles that produce dense smoke are barred, as they can impair visibility for other drivers. Overloaded or excessively heavy vehicles that pose a danger to both other traffic and the road infrastructure are also prohibited.

Vehicles must comply with the highway authority's rules and constraints to be allowed on the highways. Failure to do so puts the lives of the vehicle's occupants and other road users at risk. Machine learning, with its ability to learn from data and observations, can be utilized to recognize and identify prohibited vehicles attempting to access the highway network.

The learning process involves both supervised and unsupervised techniques. Supervised machine learning algorithms can be applied to label examples based on past experiences, enabling the prediction of future events. This approach can be employed to recognize vehicles using supervised learning methods.

Literature review

The reduction of greenhouse gas emissions is one of the main concerns[10]. Vehicles that emit carbon gasses are dangerous for the environment as well as for other drivers. The imposed gap of emissions of these gases many companies are forced to adopt clean and modern technologies to adapt Electric Vehicles to reduce these gases from the atmosphere. These recent technologies[11] are gaining interest from companies as well as researchers. Electric vehicles have several qualities such as zero emissions of gases, they are silent, and required less regular maintenance. These vehicles have a fixed quantity of gas emissions as compared to those that emit more gases.

In this paper, critical speed should be avoided, and static calculations must be added to a high dynamic allowance and extremely large vehicles with a weight that is exceeded should require a permit so they can be granted to cross the bridges. In [13] research includes side-by-side passenger recreational off-highway vehicles, it also includes driver seats that are a maximum of 50 inches wide and held within a chassis. These seats of vehicles are sitting low. The seats are covered by a roll cage. There are Grab handles for the protection of the passenger that is on the sides of the passenger seat. Then there is the engine of the vehicle which is powered by the seats that are connected to a transaxle. The engine, isolation mounted, and transaxle are together with an air intake for the engine. This vehicle is suitable for rough terrain travel.

There is a computer in the first vehicle that is configured to receive data or information from the second vehicle that is related to the second vehicle[14]. The data is used to determine that the second vehicle from which the data is received is at least operated autonomously. Furthermore, the computer may order the first vehicle to autonomously take an action and operate the first vehicle that is based on at least to determine the second vehicle that is being partially and autonomously operated at least.

This[15]research is about the design of a highway known as an automated highway system (AHS) that was developed more than ten years ago in California[1]. The highway program is a complex system and large system. In this system, vehicles are controlled automatically. This automated system requires advances in actuator and sensor technologies for implementation of the automated system. This system also requires large-scale analysis, design, testing, and simulation. It is a hierarchical control system and a hybrid control system.

This study discusses the automatic following vehicle, which is a crucial component of a completely or partially automated highway system[17]. The driver will give inputs such as accept and process to an onboard vehicle control system also infrastructures and other vehicles to perform diagnostics and such appropriate commands will be provided to actuators so that it will be compatible with the Automated highway system objectives and the motion of the vehicle is safe.

There is much Considerable research on the driving of highway vehicle automation for the improvement, efficiency, and safety of operations. It also helped to reduce traffic congestion effectively[23]. As it is true that the highway environment is more structured in some ways than other environments in which the vehicles that are automated have been proposed, the complexity of road traffic as well as density still makes the sensing and control problems of road traffic challenges. Because vehicles on the highway are having staff but this staff is expected to carry the passengers and at the same time, they manage other vehicles that are carrying the passenger. In the design, the safety and reliability considerations of the control systems are more important as compared to vehicles that do not require staff.

Methodology

In this study, neural networks and deep neural networks are utilized to examine the dataset. When used to identify classes in a dataset, a basic NN can be considered an extended form of logistic regression. The input layer of a Shallow Neural Network includes all features from all training instances. The training data is multiplied by weights, and an activation function is applied in the hidden layer. Common hidden layer activation functions include ReLU, leaky ReLU, and Randomized ReLU. For binary classification problems, the sigmoid function is employed in the output layer, while the SoftMax function is used for multiclass classification. This study focuses on a binary classification problem, so the sigmoid activation function is used in the experiments. Various cost functions exist, such as MSE and RMSE, but these provide a non-convex function with multiple local minima when applied to classification tasks. As a result, the cross-entropy loss function is employed, as it has a convex form without the local minima issue. This shallow neural network serves as a benchmark to demonstrate the efficacy of the proposed model, which is termed NNBM. Fig 4.1 summarizes the different phases involved in deploying the proposed model.

Dataset

A new data set has been created to identify those outlawed or banned vehicles on highways.
This dataset, titled "Identifying Prohibited Vehicles on Highways using Deep Learning Techniques," consists of 1,600 images gathered from various sources, including newspapers, traffic police, free images from Google, and personally taken photographs. The dataset is divided into two classes: banned vehicles and allowed vehicles. The banned vehicle class includes 800 images, while the allowed vehicle class contains 800 images, resulting in a total of 1,600 images in the dataset.
The allowed vehicles in the dataset consist of images of various road-legal vehicles, such as passenger cars, buses, and commercial trucks. These vehicles are typically designed for legal use on public roads and highways. In contrast, the banned vehicles class includes images of manual vehicles like carts and rickshaws, two-wheeled vehicles, heavily modified off-road vehicles, and other types of prohibited vehicles that are not permitted on public roads and highways. These vehicles are not designed or intended for highway use and may pose safety risks if allowed on the roads. To ensure the robustness of the model, the dataset includes images taken in diverse lighting conditions, angles, and backgrounds, representing the varied real-world scenarios that the system may encounter.

Table.1: The distribution of pictures into train and test datasets and the ISDOVH categories.

Label	Category	Train	Test
1	Prohibited Vehicle	600	200
2	Allowed Vehicles	630	170

As shown in Table 1, there are two categories, each with 800 photos, giving us a total of 1600 images. Figure 1 shows a mosaic of ISDOVH images.

Fig 1: Pictures gathered from several sources

Data Normalization

To prevent such distortion, the standards of these pictures (i.e., pixel and scope) are placed keenly on a similar statistical distribution. The variety of ways that spatial and intensity characteristics might lead CNN architecture confused, the approach outlined above is normalization. Spatial normalization is used to create the same spatial connection across pictures; it includes scaling as well as linear and non-linear adjustments. In contrast, intensity normalization is the process of adjusting pixel values using the same statistical distribution.

LeNet

LeNet starts with a pair of average pooling layers, which are used to downsample the input images. This is followed by a convolutional layer with a stride of 1 and 2, respectively, to extract spatial features from the input. The network then takes a set of grayscale images with dimensions of 32x32x1 as input. Towards the end of the architecture, LeNet employs fully connected layers, where the output layer uses the SoftMax activation function to produce the final classification predictions.

AlexNet

The next architecture is called Alexa, BLC, and Leonard. Now here i'll describe AlexNet, which is one of the first of its kind. It's very complex, it was built very nicely, and this is one of the best models and best architectures. Experts say we are going to go step by step and AlexNet is believed to solve many of the voting-related problems as well based on the second place in terms of accuracy is higher as compared to its ancestors. It's a huge margin in that kind of competition and these guys are done it great. The architecture consists of three fully linked layers and five convolutional layers. One layer is the final layer, which is the output layer and it's enabled through SoftMax. AlexNet has got. Multiple convolutional layers might look like later, but it is much deeper. LeNet also had multiple convolution layers but here the numbers are large, and it is a deeper and most important point, we have got 60 million parameters. It is challenging and the 60 million, a huge number count makes it challenging and most important. Need to order development from LeNet is the depth that we can give. That is why this architecture is called a deep neural network and without any doubt, we can call it deeper. And drop out is one of the features which is added in this model and data augmentation is also done. This process, known as data augmentation, allows us to increase the number of photos in the training data set. The introduction of the GPU under storage also brings great stress and relevance to this design. The GPU began to develop and the technological revamp began to develop so that it could also provide better accuracy levels.
And this is regarded as one of the First renovations of its class. And this might be understandable in the first shot for everyone even who do not understand it. So, what we did is, we made it look easier by watching its layers. This way this is easier for anybody to understand. Even the fresher can understand how it works.
This architecture has the first Convolutional Layer which is followed by Max Pooling Layer. The second convolutional layer is followed by another Max pooling layer 3rd, 4th and 5th convolutional layers are there which do not have the Max pooling in between the four convolution layers. After the convolution layer 5, we've got another Max pooling. Now, remember, this is what is given in this way in this diagram, It is complex. Now it is time, we will understand this as well this can lay the platform for us to understand things clearly. We have one convolution layer followed by max-pooling second convolution layer followed by max-pooling 3rd, 4th, and 5th. Working of max-pooling is shown in fig 2.

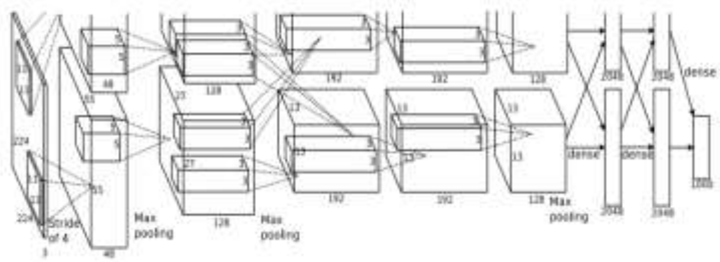


Fig 2: Max Pooling layer

Finally, followed by Max pooling and we have three fully connected layers, out of which two are fully connected layers, and the third one, the final one is nothing but the SoftMax layer. This is what is given as this complex architecture right now. The image should be of the dimension. 227 x 227 x 3. we mean we need to worry about these 227 x 227 but most of the literature is conveying it as 224 x 224 which is a mistake.
The whole process should demonstrate so that we can understand it and we can proceed with building the system after this learning. We have got dense activation, dropout, and flattened convolution. Back propagation and dropout are techniques that can be used to prevent a model from getting more fit. Over fitting can be avoided or reduced when we use dropout. Now we go with the sequential model. As usual, building a sequential neural network, remember we started the first convolution layer. We got 96 filters here. That is what we told us right at the beginning of 96 filters. The input shape is nothing, but 227 x 227 x 3 size is nothing but 11 x 11, striding is 4 and padding is

enabled, and activation is the first convolution done. Fig 3 summarize the working of whole model.

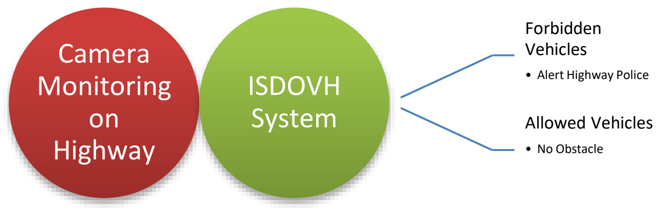


Fig 3: Proposed architecture

Results and Discussion

This research explores the use of Machine Learning to detect vehicles that are not allowed on the Pakistan Highway. The proposed ISDOVH system leverages the capabilities of the AlexNet model to effectively identify prohibited vehicles. Experimental results show that AlexNet outperforms other models like LeNet in terms of accuracy, ROC, and confusion matrix, making it a suitable choice for this application.

Analysis of Models

AlexNet is a pioneering deep learning architecture in computer vision. It is a complex and well-designed model, considered one of the best architectures of its time. Experts believe that AlexNet outperforms its predecessors in terms of accuracy, with a significant margin in competition.
The AlexNet architecture consists of three fully connected layers and five convolutional layers. One layer is the final output layer, enabled through the SoftMax function. Compared to the previous LeNet architecture, AlexNet has a larger number of convolutional layers and a deeper overall structure, with around 60 million parameters.
The depth of AlexNet, which is why it is considered a deep neural network, is a key advancement from LeNet. AlexNet also employs techniques like dropout and data augmentation to address overfitting. The introduction of GPU-powered computing further enhanced the performance of this architecture.
While AlexNet's complex structure may seem daunting at first, understanding its layers can provide a clear understanding of how it works. The architecture starts with a convolutional layer followed by max-pooling, and this pattern repeats for several convolutional layers before the final fully connected layers.
The proposed ISDOVH system leverages the capabilities of the AlexNet model to detect prohibited vehicles on highways. Experimental results show that AlexNet outperforms other models like LeNet in terms of accuracy, ROC, and confusion matrix, making it a suitable choice for this application.

Accuracy

Trained data is used to train Convolutional Neural Network models, while the model is adjusted and retrained to optimize the output using authentication data.

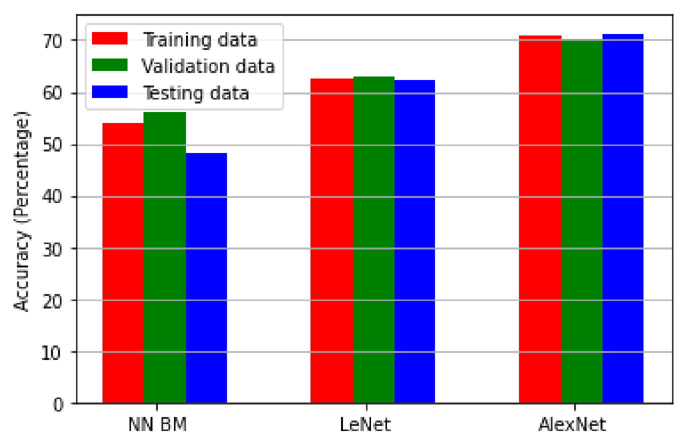


Fig 4: Accuracy in % of models

The trained model is ultimately utilized to forecast desired things from test data. Figure 4 shows the percentage accuracy of three models, revealing that AlexNet model is used accuracy for the fraction of correct predictions

ROC

An ROC curve (receiver operating characteristic curve) is a graph showing the performance of a classification model at all classification thresholds.

As shown in fig 5, this curve plots two parameters: True Positive Rate. False Positive Rate

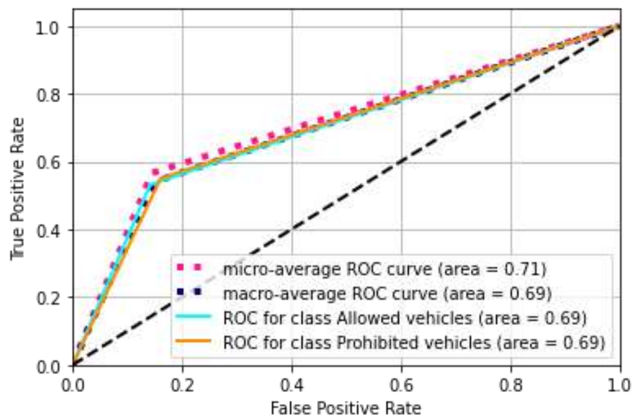


Fig 5: ROC of AlexNet

Confusion Matrix

A confusion matrix is a technique for summarizing the performance of a classification algorithm. Classification accuracy alone can be misleading if you have an unequal number of observations in each class, as shown in fig 6.

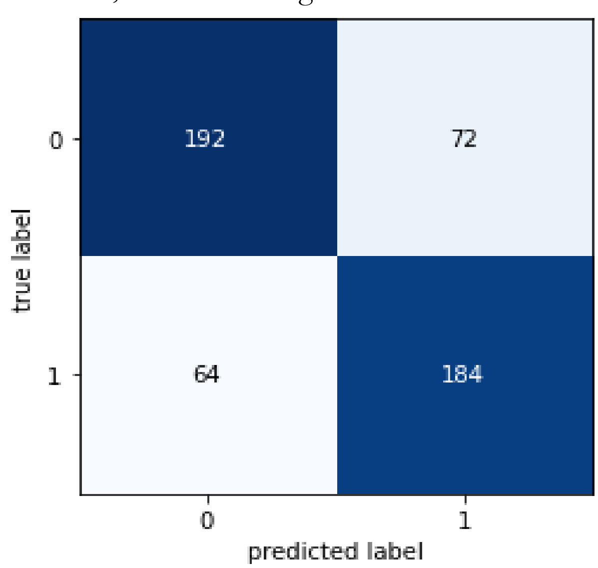
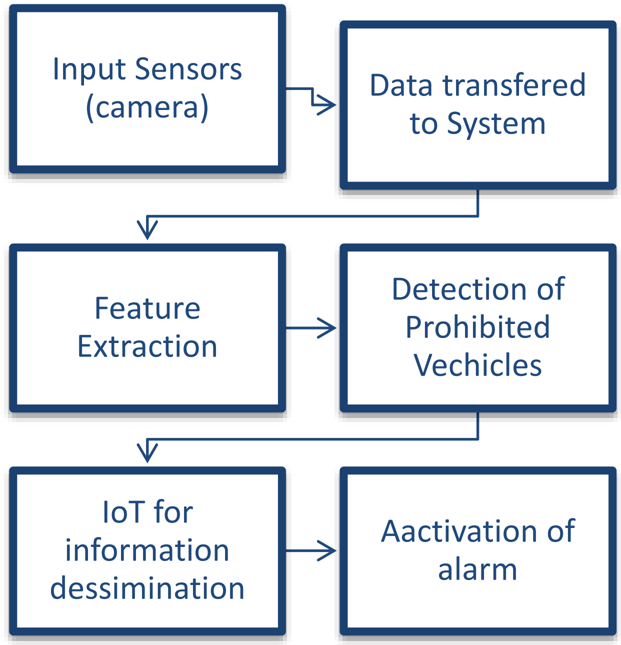


Fig 6: Confusion matrix

The Application of ISDOVH

The ISDOVH system works in conjunction with a number of different devices, featuring a functioning CCTV camera, a live internet connection, and an alarm system (depending upon the situation and needs). Through an active communication link, information is collected from



the CCTV system. The machine where it is installed receives this video feed as shown in fig 7.

Fig 7: Process Model of ISDOVH

The frames are analyzed and then pre-trained. AlexNet is run characteristics from video frames extracted, enabling the videos ISDOVH to detect vehicles. A warning mechanism is initiated when the desired object (prohibited vehicle) is spotted. This alerting system is connected to many security systems, including automated calls to law enforcement and security services, the activation of panic alarms in the immediate vicinity, and automatic barrier closures to address the issue. Fig 8 shows all prohibited vehicles for highways like a motorway.

Fig 8: Detection procedure outcome

Conclusion and Future Work

This research explores the use of Machine Learning to detect vehicles that are not allowed on the Pakistan Highway. Initially, the model will be trained to identify both allowed and prohibited vehicles on the Highway. The training process requires complex mechanisms to achieve higher efficiency. The extensive contributions in defining the requirements specification ensure the development of a comprehensive solution.

In this research, we have investigated the technique of using Machine Learning to detect prohibited vehicles on the Pakistan Highway. A live system will monitor each vehicle entering the highway, and for any prohibited vehicles, the system will automatically inform the concerned authorities in real-time.

The major objectives of this research are:

- Monitor Vehicles
- Differentiate between allowed and prohibited vehicles
- Operate 24/7 online
- Provide an alert mechanism for the concerned authorities
- Ensure the safety of the highway

Recent research has developed a variety of strategies for the categorization and detection of vehicles using numerous machine learning techniques, particularly deep learning. Compared to other technologies, CNN and its variations have proven to be the most effective in identifying vehicles in both still and moving photos. The ISDOVH system has been built using AlexNet and LeNet, which have been trained and tested.

The results show that the ISDOVH system effectively detects prohibited vehicles on highways using an AlexNet-based architecture, outperforming other models like LeNet in terms of accuracy, ROC, and confusion matrix.

In the future, we plan to enhance the ISDOVH system by incorporating additional functionalities, such as the ability to identify specific types of prohibited vehicles, integrate it with existing traffic management systems, and explore the potential of emerging deep learning models for further performance improvements.

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