RES MILITARIS

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AI- POWERED ENHANCED ROAD SAFETY MANAGEMENT SYSTEMS- TRAFFIC CONGESTION RECOGNITION AND ACCIDENT DETECTION

P Deepthi, B Gnaneswari, Ramesh Artham

Assistance Professor, Assistance Professor, Assistance Professor

Dept of CSE

Sree Dattha Institute of Engineering and Science

ABSTRACT

Intelligent road traffic monitoring requires efficient systems to handle the vast amount of data generated by traffic surveillance cameras every second. Manual monitoring of this data is labor-intensive and impractical, necessitating the adoption of automated solutions. The existing method requires a huge amount of hardware equipment's deployed to the road. Moreover, they are very sensitive to the external noise and environmental conditions. It is more accurate when processing a limited number of vehicles, but it does not work well on large scale dataset. To address this challenge, a deep learning approach using Convolutional Neural Networks (CNNs) can be leveraged for traffic monitoring and control. The primary objective of this work is to develop a fast and accurate traffic detection system that significantly reduces the need for human intervention. In this proposed work, we focus on accident detection and traffic flow analysis as key components of an intelligent road traffic monitoring system. The traffic surveillance data is pre-processed to construct a comprehensive training dataset. Using this dataset, we create a specialized CNN architecture by transferring a pre-trained network to traffic-related applications and retraining it with our self-established data. By utilizing the CNN, the system can effectively classify various multiclass problems, including accident detection, and identifying dense or sparse traffic conditions.

INTRODUCTION

1.1 Overview

Accident detection and traffic flow analysis are essential components of intelligent road traffic monitoring systems, contributing significantly to enhancing road safety, reducing congestion, and improving overall traffic management. These systems use a combination of advanced technologies and data analytics to achieve their objectives.

Accident detection systems employ a variety of sensors and cameras strategically placed along roadways to monitor traffic conditions in real-time. These sensors can detect sudden changes in vehicle speed, unexpected stops, and anomalies in traffic patterns, which may indicate an accident or a potential hazard. Once an incident is detected, the system can alert authorities, such as the traffic management center or emergency services, enabling rapid response and potentially saving lives. Additionally, these systems often use machine learning algorithms to analyze historical accident data to predict accident-prone areas, allowing for proactive safety measures.

Traffic flow analysis, on the other hand, focuses on understanding and optimizing the movement of vehicles on the road. This involves collecting and processing vast amounts of data from various sources, including traffic cameras, GPS devices, and vehicle sensors. By analyzing this data, traffic management systems can provide real-time information to drivers through digital signs, mobile apps, or navigation systems, helping them make informed decisions about their routes and reducing congestion. Traffic flow analysis also assists transportation agencies in making data-driven decisions about road design, infrastructure improvements, and traffic signal optimization to improve overall traffic efficiency.

Intelligent road traffic monitoring systems often integrate accident detection and traffic flow analysis into a unified platform. This integration allows for a holistic view of traffic conditions and enables more effective traffic management. For example, when an accident is detected, the system can automatically adjust traffic signals, reroute traffic, or provide alternative routes to minimize disruptions. It can also help emergency responders reach the scene faster by dynamically clearing traffic paths.

So, accident detection and traffic flow analysis are critical components of intelligent road traffic monitoring systems that leverage technology and data analysis to enhance road safety, reduce congestion, and optimize traffic flow. These systems play a pivotal role in improving transportation efficiency and overall quality of life for commuters by ensuring smoother traffic operations and quicker response to incidents on the road.

1.2 Research Motivation

The motivation for conducting research in the field of accident detection and traffic flow analysis for intelligent road traffic monitoring is driven by the pressing need to address the ever-increasing challenges posed by urbanization, population growth, and escalating traffic congestion in modern cities and regions worldwide. This research area has become more critical than ever due to its potential to revolutionize the way we manage and optimize our transportation systems. Several key motivations underscore the significance of research in this domain.

Firstly, road traffic accidents continue to be a major global concern, resulting in a significant loss of life, property damage, and economic costs. Developing advanced accident detection systems can substantially reduce response times for emergency services, leading to a higher likelihood of saving lives and minimizing the severity of injuries. By proactively identifying accident-prone areas and implementing preventive measures, such as improved road design or traffic signal optimization, we can reduce the frequency and severity of accidents, contributing to enhanced road safety.

1.3 Problem Statement

The problem statement for research in the field of accident detection and traffic flow analysis for intelligent road traffic monitoring revolves around the multifaceted challenges associated with modern urban transportation systems. As cities grow and road networks become increasingly congested, there is an urgent need to address the following key issues:

- **Road Safety**: One of the most pressing problems is the persistently high rate of road traffic accidents, which result in loss of life, injuries, and extensive property damage. The problem statement underscores the need for more effective accident detection systems that can swiftly identify incidents and notify emergency services to minimize response times. Additionally, there is a need to identify accident-prone areas through data analysis and proactively implement safety measures.
- **Traffic Congestion**: Traffic congestion continues to plague urban areas, causing significant economic losses, wasted time, and environmental pollution. The problem statement emphasizes the necessity of traffic flow analysis to alleviate congestion. This involves providing commuters with real-time traffic information to make informed decisions about

their routes and encouraging the implementation of intelligent traffic management solutions to optimize traffic signal timings and reduce gridlock.

1.4 Applications

The applications of accident detection and traffic flow analysis in intelligent road traffic monitoring are far-reaching and have the potential to transform the way we manage and interact with our transportation systems. Here are detailed descriptions of some key applications:

- **Real-time Traffic Management**: Accident detection and traffic flow analysis systems provide real-time insights into traffic conditions. Traffic management authorities can use this information to dynamically adjust traffic signals, manage lane closures, and reroute vehicles to minimize congestion and maintain smooth traffic flow. This application helps reduce travel times and fuel consumption for commuters.
- **Accident Response and Emergency Services**: Perhaps one of the most critical applications is the swift response to accidents and emergencies. These systems can automatically detect accidents, pinpoint their locations, and notify emergency services immediately. This leads to faster response times, potentially saving lives and reducing the severity of injuries.
- **Predictive Analytics**: By analyzing historical traffic data, these systems can predict congestion and accident-prone areas. This application enables traffic management authorities to implement preemptive measures such as adjusting traffic patterns, optimizing road designs, and deploying additional resources in high-risk zones.
- **Navigation and Route Optimization**: For commuters, navigation apps can integrate real-time traffic data to offer alternative routes to avoid congestion and accidents. This application enhances the overall travel experience, reduces travel time, and minimizes the frustration associated with traffic jams.
- **Public Transportation Management**: Public transportation systems benefit from traffic flow analysis by improving bus and train schedules to accommodate traffic conditions. This ensures that public transportation remains a viable and efficient option, even during peak traffic hours.

2.LITERATURE SURVEY

With the rapid development of today's society, the number of cars increases dramatically. Traffic accidents have also increased, resulting in huge human and economic losses (Micheale [1]). According to the World Health Organization, road traffic accidents kill more than 1.25 million people each year, and nonfatal accidents affect more than 20 to 50 million people (Bahiru et al. [2]). It can be seen that road traffic accidents have become one of the leading causes of death and injury worldwide. How to prevent traffic accidents and how to predict traffic accidents has become a hot topic in traffic science and intelligent vehicle research. The severity of traffic accidents is an important index of traffic accident harm. There are various factors that cause traffic accidents of different degrees. Many algorithms and factors have been cited in the study of traffic accidents.

Lu et al. [3] analyzed the location of a car in road transects, the road safety grade, the road surface condition, the visual condition, the vehicle condition, and the driver state were studied, and the prediction accuracy model of 86.67% was established. Alkheder et al. [4] predicted the severity of traffic accidents from 16 attributes and four injury degrees (minor, moderate, severe, and death) through artificial neural networks.

Akanbi et al. [5] found that old age, overtaking, speeding, religious beliefs, poor braking performance, and bad tires were the main human factors causing and causing plant and animal extinctions in traffic accidents. Some effects of weather and accident conditions on the characteristics of highway traffic behavior have also been pointed out by Caleffi et al. [6]. An et al. [7] applied a fuzzy convolutional neural network to traffic flow prediction under uncertain traffic accident information and verified its effectiveness through the real trajectory of cars and meteorological data. Multiobjective genetic algorithms have also achieved good results in predicting the severity of traffic accidents according to users' preferences (Hashmienejad and Hashmienejad [8]).

The deep learning method obtained a short-term traffic accident risk prediction model through traffic accidents, traffic flow, weather conditions, and air pollution (Ren et al. [9]). The spatio-temporal correlation of traffic accidents has been proposed in urban traffic accident risk prediction (Ren et al. [10]).

3.PROPOSED SYSTEM

3.1 Overview

The traffic surveillance system accumulates an enormous amount of data regarding road traffic each second. Monitoring these data with the human eye is a tedious process and it also requires manpower for monitoring. A deep learning approach can be utilized for traffic monitoring and control. The traffic surveillance data are pre-processed to construct the training dataset. The Traffic net is constructed by transferring the network to traffic applications and retraining it with a self-established data set. This Traffic net can be used for regional detection in large scale applications. Further, it can be implemented across-the-board. The efficiency is admirably verified through speedy discovery in the high accuracy in the case study. The tentative assessment could pull out to its successful application to a traffic surveillance system and has potential enrichment for the intelligent transport system in future.

The block diagram of the proposed method, as shown in Figure 4.1, outlines the various steps involved in the process of traffic status prediction using a Deep Learning Convolutional Neural Network (DLCNN) on the TrafficNet dataset. Here's a detailed explanation of each step:

3.2 Proposed DLCNN

Deep neural network is gradually applied to the identification of crop Traffic conditions and insect pests. Deep neural network is designed by imitating the structure of biological neural network, an artificial neural network to imitate the brain, using learnable parameters to replace the links between neurons. Convolutional neural network is one of the most widely used deep neural network structures, which is a branch of feed forward neural network. The success of DLCNN network model also confirms the importance of convolutional neural network model. Since then, convolutional neural networks have developed vigorously and have been widely used in financial supervision, text and speech recognition, smart home, medical diagnosis, and other fields.

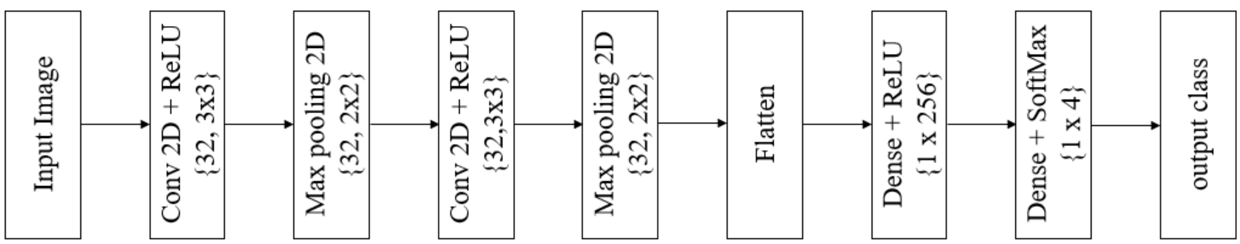


Fig. 3.1: Proposed DLCNN

Table.1: Layers description.

Layer Names	No. of filters	Kernel size	Feature size
Conv 2D +ReLU	32	3 x 3	62x62x32
Max pooling 2D	-	3 x 3	31x31x32
Conv 2D+ReLU	32	3 x 3	29x29x32
Max pooling 2D	-	3 x 3	14x14x32
Flatten	-	1x6272	1x6272
Dense +ReLU		1 x 256	1 x 256
Dense + SoftMax		1 x 4	1 x 4

Convolutional neural networks are generally composed of three parts. Convolution layer for feature extraction. The convergence layer, also known as the pooling layer, is mainly used for feature selection. The number of parameters is reduced by reducing the number of features. The full connection layer carries out the summary and output of the characteristics. A convolution layer is consisting of a convolution process and a nonlinear activation function ReLU. A typical architecture of CNN model for crop Traffic condition recognition is shown in Figure 2.

The leftmost image is the input layer, which the computer understands as the input of several matrices. Next is the convolution layer, the activation function of which uses ReLU. The pooling layer has no activation function. The combination of convolution and pooling layers can be constructed many times. The combination of convolution layer and convolution layer or convolution layer and pool layer can be very flexibly, which is not limited when constructing the model. But the most common CNN is a combination of several convolution layers and pooling layers. Finally, there is a full connection layer, which acts as a classifier and maps the learned feature representation to the sample label space.

Convolutional neural network mainly solves the following two problems.

1) Problem of too many parameters: It is assumed that the size of the input picture is $50 * 50 * 3$. If placed in a fully connected feedforward network, there are 7500 mutually independent links to the hidden layer. And each link also corresponds to its unique weight parameter. With the increase of the number of layers, the size of the parameters also increases significantly. On the one hand, it will easily lead to the occurrence of over-fitting phenomenon. On the other hand, the neural network is too complex, which will seriously affect the training efficiency. In convolutional neural networks, the

parameter sharing mechanism makes the same parameters used in multiple functions of a model, and each element of the convolutional kernel will act on a specific position of each local input. The neural network only needs to learn a set of parameters and does not need to optimize learning for each parameter of each position.

2) Image stability: Image stability is the local invariant feature, which means that the natural image will not be affected by the scaling, translation, and rotation of the image size. Because in deep learning, data enhancement is generally needed to improve performance, and fully connected feedforward neural is difficult to ensure the local invariance of the image. This problem can be solved by convolution operation in convolutional neural network.

Convolution layer: According to the facts, training and testing of DLCNN involves in allowing every source image via a succession of convolution layers by a kernel or filter, rectified linear unit (ReLU), max pooling, fully connected layer and utilize SoftMax layer with classification layer to categorize the objects with probabilistic values ranging from [0,1].

Convolution layer as depicted in Figure 4.3 is the primary layer to extract the features from a source image and maintains the relationship between pixels by learning the features of image by employing tiny blocks of source data. It’s a mathematical function which considers two inputs like source image $I(x, y, d)$ where x and y denotes the spatial coordinates i.e., number of rows and columns. d is denoted as dimension of an image (here $d = 3$, since the source image is RGB) and a filter or kernel with similar size of input image and can be denoted as $F(k_x, k_y, d)$.

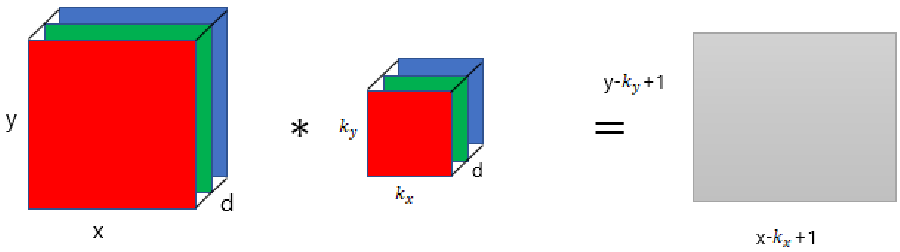


Fig. 3.3: Representation of convolution layer process.

The output obtained from convolution process of input image and filter has a size of $C\left((x - k_x + 1), (y - k_y + 1), 1\right)$, which is referred as feature map. An example of convolution procedure is demonstrated in Figure 4(a). Let us assume an input image with a size of 5×5 and the filter having the size of 3×3. The feature map of input image is obtained by multiplying the input image values with the filter values as given in Figure 4 (b).

1	1	1	0	0
0	0	1	1	1
1	1	0	0	1
0	0	0	1	1
1	1	1	0	0

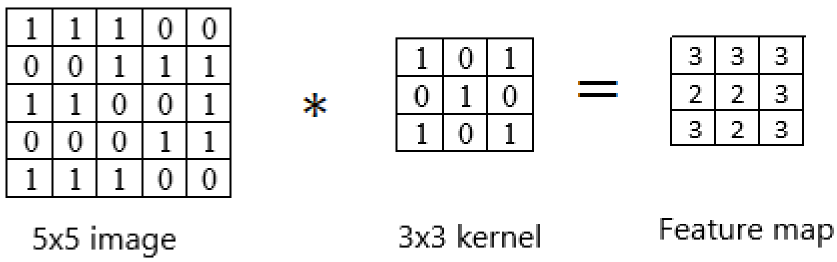
5x5 image

*

1	0	1
0	1	0
1	0	1

3x3 kernel

(a)



(b)

Fig. 4.4: Example of convolution layer process (a) an image with size **5** × **5** is convolving with **3** × **3** kernel (b) Convolved feature map

ReLU layer: Networks those utilizes the rectifier operation for the hidden layers are cited as rectified linear unit (ReLU). This ReLU function $\mathcal{G}(\cdot)$ is a simple computation that returns the value given as input directly if the value of input is greater than zero else returns zero. This can be represented as mathematically using the function $max(\cdot)$ over the set of 0 and the input x as follows:

$$\mathcal{G}(x) = \max\{0, x\}$$

Max pooing layer: This layer mitigates the number of parameters when there are larger size images. This can be called as subsampling or down sampling that mitigates the dimensionality of every feature map by preserving the important information. Max pooling considers the maximum element form the rectified feature map.

SoftMax classifier: Generally, softmax function is added at the end of the output as shown in Figure 5, since it is the place where the nodes are meet finally and thus, they can be classified. Here, X is the input of all the models and the layers between X and Y are the hidden layers and the data is passed from X to all the layers and Received by Y. Suppose, we have 10 classes, and we predict for which class the given input belongs to. So, for this what we do is allot each class with a particular predicted output. Which means that we have 10 outputs corresponding to 10 different class and predict the class by the highest probability it has.

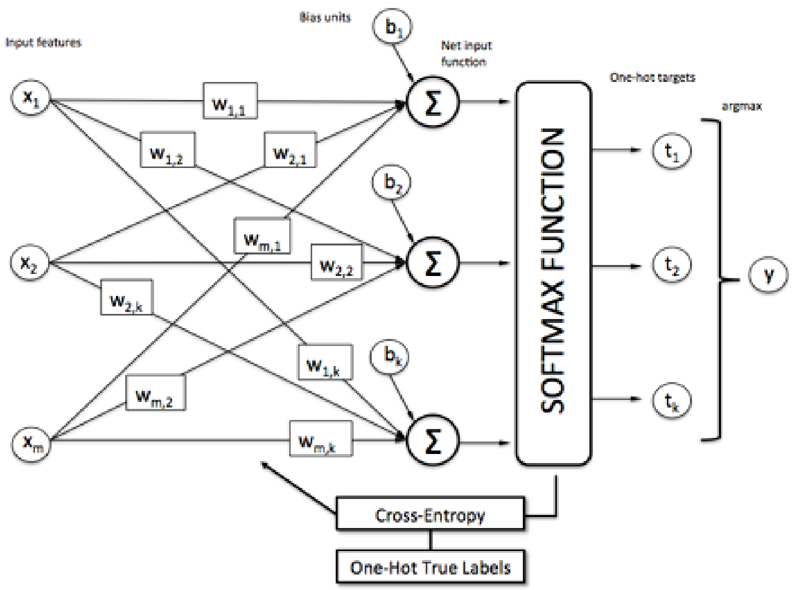


Fig.3.4: Traffic condition prediction using SoftMax classifier.

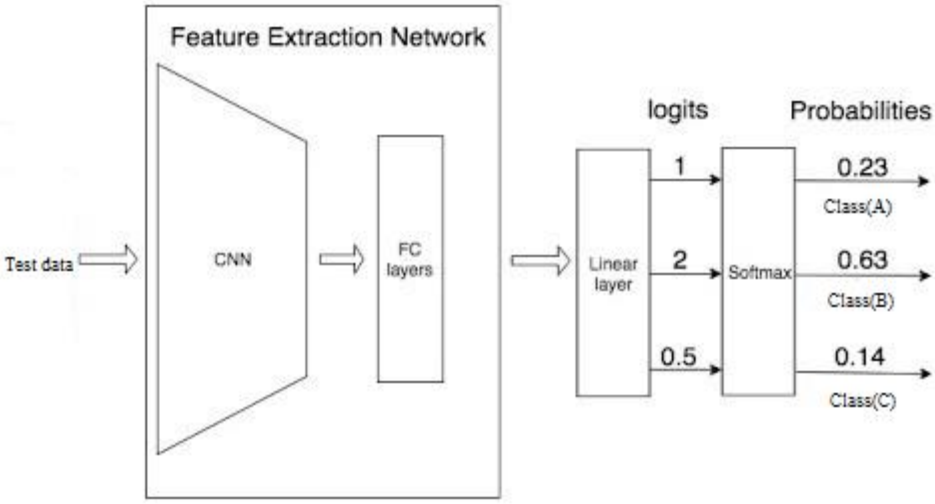


Fig.3.5: Example of SoftMax classifier.

In Figure 6, and we must predict what is the object that is present in the picture. In the normal case, we predict whether the crop is A. But in this case, we must predict what is the object that is present in the picture. This is the place where softmax comes in handy. As the model is already trained on some data. So, as soon as the picture is given, the model processes the pictures, send it to the hidden layers and then finally send to softmax for classifying the picture. The softmax uses a One-Hot encoding Technique to calculate the cross-entropy loss and get the max. One-Hot Encoding is the technique that is used to categorize the data. In the previous example, if softmax predicts that the object is class A then the One-Hot Encoding for:

Class A will be [1 0 0]

Class B will be [0 1 0]

Class C will be [0 0 1]

From the diagram, we see that the predictions are occurred. But generally, we don't know the predictions. But the machine must choose the correct predicted object. So, for machine to identify an object correctly, it uses a function called cross-entropy function.

So, we choose more similar value by using the below cross-entropy formula.

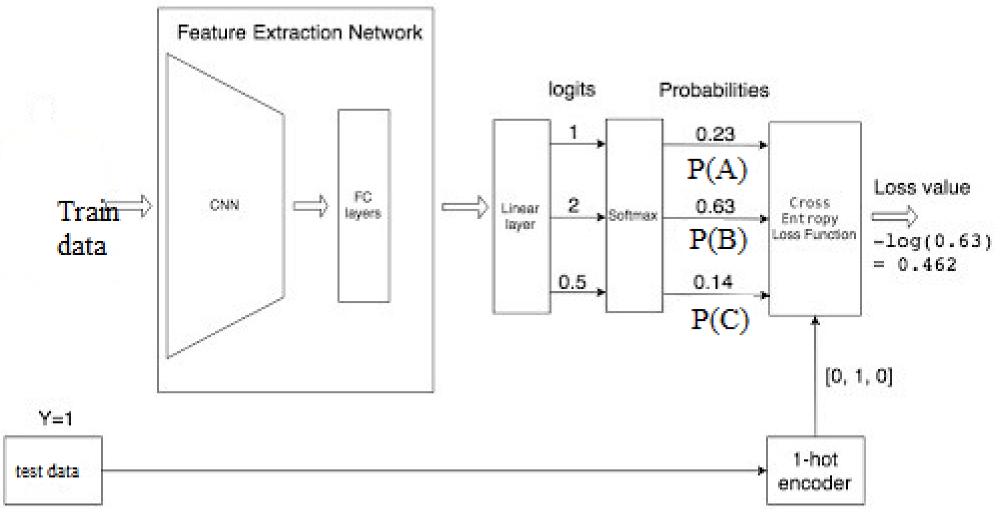


Fig.3.6: Example of SoftMax classifier with test data.

In the above example we see that 0.462 is the loss of the function for class specific classifier. In the same way, we find loss for remaining classifiers. The lowest the loss function, the better the prediction is. The mathematical representation for loss function can be represented as: -

$$LOSS = np.sum(-Y * np.log(Y\_pred))$$

4.5 Advantages

The proposed method for traffic status prediction using a Deep Learning Convolutional Neural Network (DLCNN) on the TrafficNet dataset offers several significant advantages:

- **Accuracy and Precision**: DLCNNs are renowned for their ability to extract intricate patterns and features from images, making them highly effective in classifying complex traffic conditions. This results in a high level of accuracy and precision in predicting traffic statuses, which is crucial for reliable traffic management and safety assessments.
- **Automation**: The method automates the process of traffic status prediction, eliminating the need for manual monitoring and assessment. This automation can save valuable time and resources while providing real-time insights into traffic conditions, which is particularly useful in urban areas with heavy traffic.
- **Scalability**: Deep learning models, including DLCNNs, can handle large datasets efficiently. As traffic data continuously accumulates, the method can easily scale to accommodate more data without a significant increase in computational complexity, allowing for continuous improvement in prediction accuracy.
- **Adaptability**: DLCNNs can adapt to changing traffic patterns and conditions. As traffic dynamics evolve due to factors like weather, accidents, and special events, the model can continuously learn and adjust its predictions, ensuring it remains relevant and accurate over time.
- **Safety Enhancement**: Accurate traffic status prediction is instrumental in enhancing road safety. By quickly identifying accidents or fires on the road, emergency services can be alerted promptly, potentially saving lives and reducing the severity of injuries. This is a critical advantage for public safety and emergency response.
- **Data-Driven Insights**: The method generates valuable data-driven insights into traffic conditions. By analyzing the predictions and performance metrics, transportation authorities and urban planners can gain a deeper understanding of traffic patterns, accident hotspots, and areas prone to congestion, enabling them to make informed decisions for traffic management and infrastructure improvements.
- **Cost Efficiency**: The automated nature of the method can lead to cost savings in terms of manpower and resources required for manual traffic monitoring. It allows transportation agencies to allocate their resources more efficiently and effectively.
- **Real-Time Monitoring**: The method provides real-time traffic status updates, enabling commuters to make informed decisions about their routes, ultimately reducing travel time and fuel consumption. Additionally, it aids in dynamic traffic signal control, helping to minimize congestion and improve traffic flow in real-time.

- **Environmental Benefits**: By reducing traffic congestion and optimizing traffic flow, the method indirectly contributes to reduced greenhouse gas emissions and improved air quality, aligning with sustainability and environmental goals in urban areas.
- **Continuous Improvement**: The model can be continuously fine-tuned and improved as more data becomes available, leading to even more accurate predictions over time. This adaptability ensures that the method remains effective in evolving traffic scenarios.

4.RESULTS AND DISCUSSION

Fig.1: Uploading of Image Dataset in the Accident Detection GUI.

Fig.2: Accuracy of CNN model.

Figure 2 indicates that the classifier has made a prediction, and the outcome of that prediction is "low traffic." In other words, when the classifier was presented with a specific input or data instance, it classified the traffic condition associated with that instance as "low traffic."

Figure 3 presents a different prediction outcome. In this case, the classifier's prediction is "heavy traffic." This suggests that, based on the features or attributes of the input data it was provided, the classifier determined that the traffic condition was characterized by congestion or heavy traffic flow.

Figure 4 illustrates yet another prediction result. Here, the classifier's prediction outcome is "accident occurred." This implies that the classifier recognized specific patterns or indicators in the input data that led it to classify the traffic condition as one in which an accident had taken place.

Fig.2: Predicted outcome as low traffic

Fig.3: Predicted outcome as classifier predicted as heavy traffic

Fig.4: Predicted outcome as classifier predicted as accident occurred.

Indicates that the content of Figure 5 is related to the predictions made by a classifier. Specifically, the classifier has predicted that a "fire accident occurred" based on the input data or features it was provided. This suggests that the classifier has identified certain patterns or characteristics in the data that led it to classify the situation as a fire-related accident within the traffic context.

Figure 6 contain the information about the accuracy and loss estimation for the proposed method during its training. This indicates that the figure will display two key metrics: accuracy and loss. Accuracy typically measures the proportion of correctly classified instances, while loss reflects how well or poorly the model is performing during training. This suggests that the training process was conducted for a total of 10 epochs. An epoch represents one complete pass through the entire training dataset. Training a model for multiple epochs allows it to learn and adjust its parameters over time. The graph specifies the colors used in the chart or graph to represent the accuracy and loss values. The accuracy values are typically plotted using a green line, while the loss values are represented with a red line. These lines will show how accuracy and loss change over the course of the 10 training epochs.

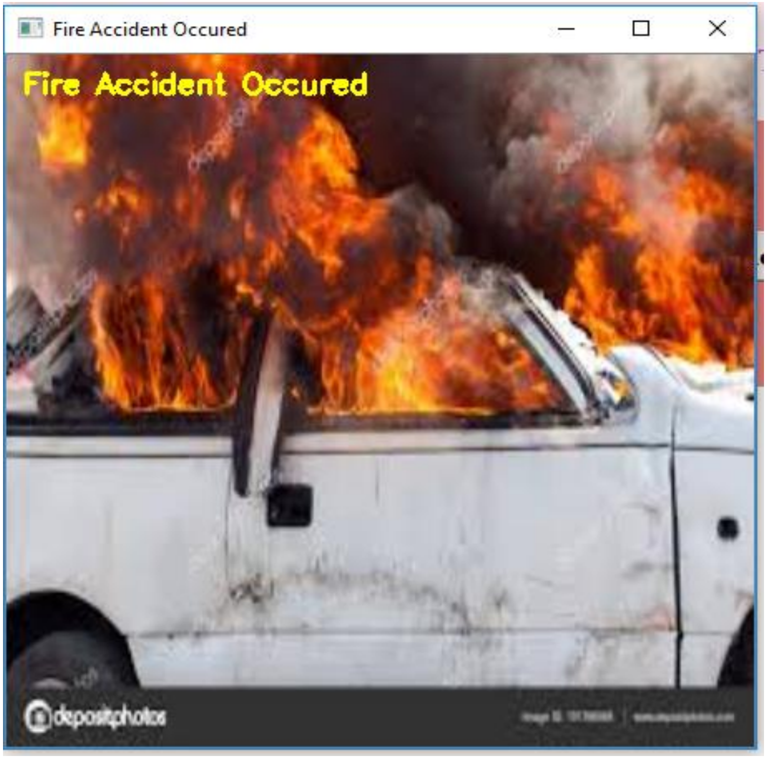


Fig.5: Predicted outcome as classifier predicted as fire accident occurred.

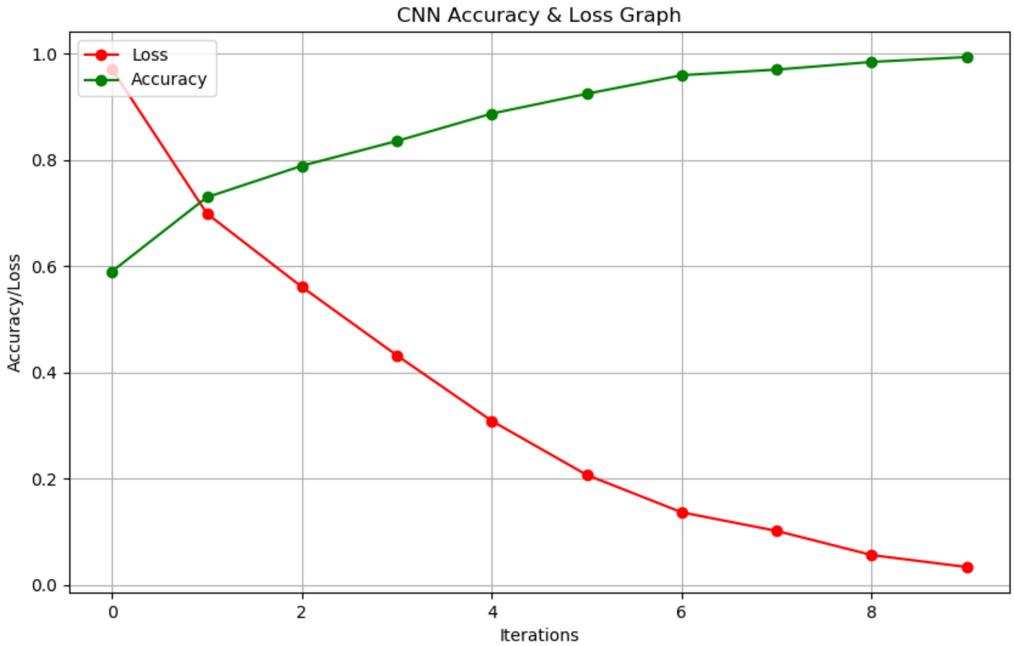


Fig.6: Accuracy and loss estimation of proposed method.

Accuracy (%): The subsequent columns provide accuracy values, expressed as percentages, for each of the methods. Accuracy is a common performance metric in classification tasks and represents the proportion of correctly predicted instances out of the total instances in the dataset.

Proposed DLCNN Accuracy: The proposed Deep Learning Convolutional Neural Network (DLCNN) achieved an impressive accuracy of 99.3%.

Table.1: Performance comparison.

Method	Proposed DLCNN
Accuracy (%)	99.3
Loss	0.183

5. CONCLUSION

5.1 Conclusion

In conclusion, the proposed method for traffic status prediction using DLCNN on the TrafficNet dataset presents a promising approach to addressing the challenges of traffic management, safety, and urban planning. This method harnesses the power of deep learning to accurately classify traffic conditions, offering advantages such as automation, scalability, and real-time monitoring. By providing precise insights into traffic dynamics, it enhances road safety, reduces congestion, and contributes to more efficient transportation systems. The model's adaptability and potential for continuous improvement make it a valuable tool for addressing the ever-evolving challenges of urban traffic. As cities continue to grow and traffic complexity increases, the significance of such methods cannot be overstated, offering a path towards smarter and safer urban mobility.

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