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Accidents Detection and Traffic Flow Analysis for Intelligent Road Traffic Monitoring

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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 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.

Keywords: Traffic condition monitoring, accident detection, computer vision, deep learning.

1. INTRODUCTION

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

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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.

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]).

The temporal aggregation neural network layer developed by Huang et al. [11] automatically captures correlation scores from the temporal dimension to predict the occurrence of traffic accidents. Kumeda et al. [12] revealed that Lighting Conditions, 1st Road Class & No., and Number of vehicles are the key features in electing the attributes. Driver behavior was effectively analyzed by Murphey et al. [13] through data mining methods. Bao et al. [14] also proposed an accident prediction model based on uncertainty and spatio-temporal relationship learning. Yaman et al. [15] use fuzzy data mining technology to analyze the factors affecting the injury degree of traffic accidents. Examples include age, gender, seatbelt use, alcohol, and drug involvement. Independent importance standardized variables affecting injury factors were obtained. A variety of algorithms have been applied to the prevention and prediction of traffic accidents. In recent years, the use of random forest algorithm in traffic accident data processing has gradually increased.

3. PROPOSED SYSTEM

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:

step 1: Dataset Splitting: The process begins with the TrafficNet dataset, which presumably contains various images or data samples related to traffic conditions. The first step is to split this dataset into two subsets: a training set and a testing set. In this case, 80% of the dataset is allocated for training, while the remaining 20% is reserved for testing. This partitioning allows the model to learn from a portion of the data and evaluate its performance on unseen data.

step 2: Dataset Preprocessing: Before the data is fed into the neural network, preprocessing operations are applied to ensure that it is in a suitable format for training and testing. The primary preprocessing operation mentioned is normalization, which typically involves scaling the data to have a consistent range of values. This step helps improve the training process by ensuring that different features or attributes do not have vastly different scales, which could hinder convergence during training.

step 3: Image Preprocessing: Since the dataset likely contains images, an image preprocessing operation is performed. This operation aims to standardize the images by resizing them to a uniform size. Standardizing the image size is crucial for ensuring that the input dimensions are consistent for all images, allowing the neural network to process them efficiently.

step 4: DLCNN for Traffic Status Prediction: The core of the proposed method is the DLCNN, which is used for predicting traffic status. A DLCNN is a type of neural network that excels at processing images and extracting meaningful features from them. In this context, the DLCNN is trained on the preprocessed training data to learn patterns and features associated with different traffic statuses, such as dense traffic, low traffic, accidents, and fires.

step 5: Traffic Status Prediction: After the DLCNN is trained, it is utilized to predict the traffic status of the test samples. These test samples are the previously reserved 20% of the dataset that the model has never seen during training. The DLCNN takes the preprocessed test images as input

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and generates predictions for each image, classifying them into one of the predefined traffic statuses (dense traffic, low traffic, accident, or fire occurred).

step 6: Performance Evaluation: The final step involves evaluating the performance of the proposed method. This evaluation assesses how well the DLCNN model can predict traffic statuses on unseen data. Common performance metrics may include accuracy, precision, recall, F1 score, and confusion matrices, among others. These metrics provide insights into the model's ability to correctly classify traffic conditions.

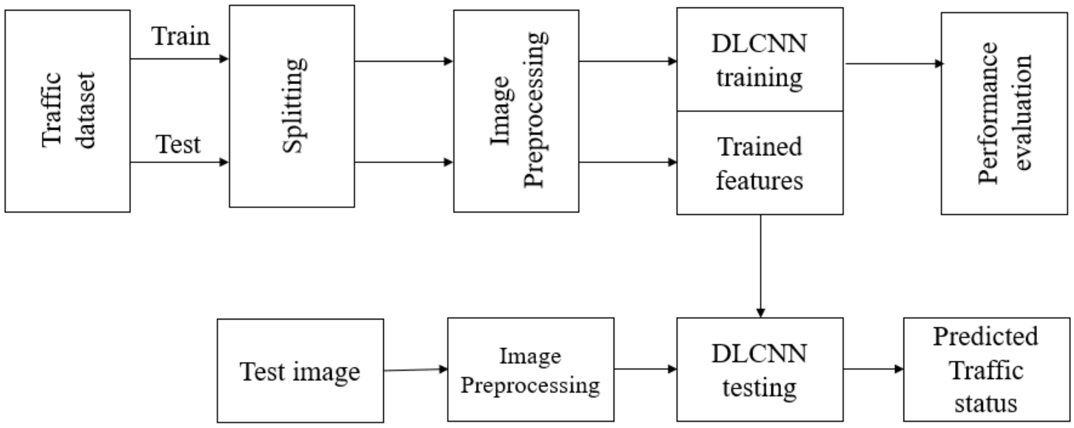

Figure 1: Proposed methodology

4. RESULTS AND DISCUSSION

The input dataset of dissimilar classes is gathered from the net. The assessment of output class is set next to the obtained dataset. Four folders namely sparse_traffic, dense_traffic, fire, accident, every folder contains 900 images are generated for training and validation purposes. The folder name represents the class value for classifying output.

- **Data Source**: The dataset is collected from the internet, indicating that it is likely a compilation of images or data samples representing various traffic conditions. These conditions may include sparse traffic, dense traffic, fire-related incidents, and accidents.
- **Class Labels**: Each data sample (or image) in the dataset is associated with a specific class label that represents the type of traffic condition it belongs to. In this case, there are four distinct class labels: "sparse_traffic," "dense_traffic," "fire," and "accident." These class labels are used for classification tasks to predict the traffic condition based on the input data.
- **Dataset Size**: The dataset is divided into four folders, each corresponding to one of the four class labels. Within each folder, there are a total of 900 images. This distribution suggests that the dataset is reasonably balanced, with an equal number of samples for each class. Such balance is often desired in machine learning to prevent bias towards any particular class.
- **Training and Validation**: The dataset appears to be further divided into training and validation sets. Training sets are typically used to train machine learning models, while validation sets are used to assess the model's performance during training and make adjustments if needed. Having separate training and validation sets helps ensure the model generalizes well to unseen data.

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- **Folder Names as Class Labels**: The folder names themselves are used as class labels, making it easy to map each image to its corresponding traffic condition class. This naming convention simplifies the dataset's organization and management.

Figure 3 presents a traffic prediction outcome. In this case, the classifier's prediction is low traffic, and 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.

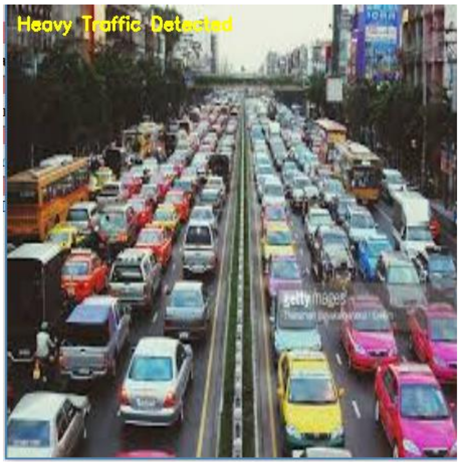

Fig. 3: Predicted outcome as low traffic (left). Predicted outcome as classifier predicted as heavy traffic (right).

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

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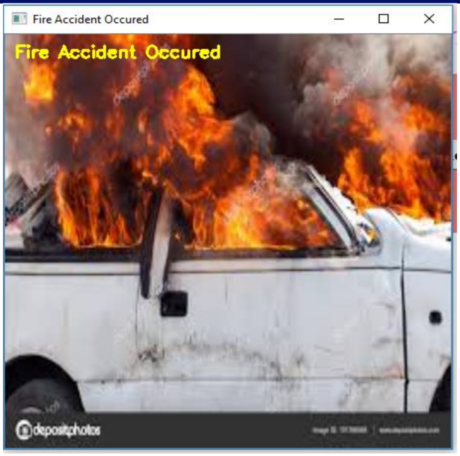

Fig. 5: Predicted outcome as classifier predicted as fire accident occurred.\ Indicates that the content of Figure 5 is related to the predictions made by a classifier. Specifically, the classifier has predicted that a "fire accident occurred" based on the input data or features it was provided. This 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.

5. 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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