Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Issue 10, October : 2024

ACCIDENT DETECTION AND LIVE IMAGE TRACKING WITH LOCATION SHARING

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Abstract— The dynamic and unpredictable nature of road traffic necessitates effective accident detection methods for enhancing safety and streamlining traffic management in smart cities. This paper offers a comprehensive exploration study of prevailing accident detection techniques, shedding light on the nuances of other state-of-the-art methodologies while providing a detailed overview of distinct traffic accident types like rear-end collisions, T-bone collisions, and frontal impact accidents. Our novel approach introduces the CNN model architecture, a lightweight solution tailored explicitly for accident detection in smart city traffic surveillance systems by integrating RGB frames with optical flow information. Empirical analysis of our experimental study underscores the efficacy of our model architecture. The -CNN (trainable) model outperformed its counterparts, achieving an impressive 87% Our findings further elaborate on the challenges posed by data imbalances, particularly when working with a limited number of datasets, road structures, and traffic scenarios. Ultimately, our research illuminates the path towards a sophisticated vision-based accident detection system primed for real-time integration into edge IoT devices within smart urban infrastructures Accident detection is a critical aspect of modern transportation systems, aimed at reducing response times and improving the chances of survival for victims. This project focuses on utilizing deep learning techniques to detect accidents in real-time. The system employs a combination of sensors and cameras to monitor vehicles' movements and detect anomalies indicative of accidents. Upon detection, the system captures images of the scene and uses google maps to track the location. These images and the precise location data are immediately transmitted to nearby hospitals and police stations to facilitate a prompt response. The integration of cloud computing ensures that data is efficiently processed and transmitted, enhancing the overall effectiveness of the emergency response. This approach not only reduces the time taken for emergency services to reach the accident site but also provides crucial visual information to first responders, enabling better preparation and resource allocation.

Index Terms— Traffic surveillance, accident detection, action recognition, smart city, autonomous transportation, deep learning

I. INTRODUCTION

There are different factors that cause traffic accidents. Among the most common factors that increase the probability of their occurrence are the geometry of the road, the climate of the area, drunk drivers, and speeding. These accidents can cause harm to the people involved and, although most of these present only material damage, each one affects people's quality of life in terms of both traffic mobility and personal safety. Thanks to technological advances, video cameras have become a resource for controlling and regulating traffic in urban areas. They make it possible to analyze and monitor the traffic flowing within the city. However, the number of cameras needed to perform these tasks has been increasing significantly over time, which makes control difficult if automation mechanisms are not implemented because the number of professionals needed to comply with all the points also increases.

Several approaches have been proposed to automate tasks within the control and follow-up process. An example of this is a system based on video camera surveillance in traffic. Through these, it is possible to estimate the speeds and trajectories of the objects of interest, with the objective of predicting and controlling the occurrence of traffic accidents in the area. The scientific community has presented different approaches to detect traffic accidents. These include statistics-based methods, social network data analysis, sensor data, machine learning, and deep learning. These latest techniques have presented improvements in various fields of science, including video-based problem solving (video processing). Therefore, it is important to study these techniques in order to approach a solution to the detection and classification of traffic accidents based on video. With the advent of convolutional layers in the domain of neural networks, better performance has been achieved in the solution of problems involving digital image processing.

Deep learning techniques have shown high performance in a large number of problems, especially for image understanding and analysis. These layers exploit the spatial relationship that the input data possess and that, due to the size of the information, it is not possible to achieve with dense neural networks. The use of convolutions on input data with a large number of features makes it possible, among other things, to avoid the problem of the curse of dimensionality. This is a very frequent problem when working with data with high complexity, such as images. Likewise, it is important to highlight that the use of several convolutional layers helps the extraction of relevant visual features within the same dataset, which defines the performance of the network. On the other hand, there are problems where the spatial relationship of the data is not a determining characteristic. In some problems, the temporal relationship that the data may have is of greater importance. This is because there are events that depend on past and/or future events, that is, on a context of the event in time in order to understand the real event. This is why a new deep learning model has emerged: recurrent neural networks. These networks have a similar architecture to dense artificial neural networks but differ in that at least one neuron has a connection to itself. This allows them to be able to remember what has been previously processed, i.e., it gives them the ability to store information over periods of time (data memory).

They specialize in finding the temporal relationships that a set of data may have. Such networks are used to solve problems such as rate-of-change prediction, text translation, and natural language processing, among the others. The data processing in these neuron has a higher complexity than the processing performed from a traditional neuron. In addition, these have been improved over the years. One of the most relevant changes was the possibility that the cell can store short- and long-term memory, called long short-term memory neurons (LSTM). These networks have presented improvements in several problems with respect to past models. Among these are travel time prediction problems, language understanding, and natural language processing. However, the analysis of video scenes is not a problem that can be solved using one of the two models mentioned above. This is because a video presents both a spatial and a temporal relationship in its content. Therefore, the scientific community has presented several architectures that use both deep learning layers: convolutional layers and recurrent layers.

Some of the advances they have achieved using these types of architectures are emotion recognition, estimation of a person's posture, analysis of basketball videos for the automation of tasks such as the score of each team and action recognition.

Because of this, a method capable of solving the traffic accident detection problem is proposed. However, the process of detecting traffic accidents is a task that involves a lot of processing and, for this reason, these tasks present many difficulties. The occurrence of a road accident is an event capable of occurring in multiple patio-temporal combinations.

This leaves a large domain of diverse distributions of data to be classified as an accident, which makes it difficult to solve the problem. Similarly, the classification of an accident is a complex problem due to the temporal implications it may present. Therefore, we seek to improve the performance of current approaches with the design of a method capable of detecting traffic accidents through video analysis using deep learning techniques.

II. LITERATURE REVIEW

The literature survey encompasses a range of studies that delve into the complexities surrounding traffic accidents, exploring various factors contributing to their occurrence and proposing methodologies for their detection and analysis Li (2004) presents a study focused on understanding road traffic dynamics through an urban traffic model of the circular working field. This research likely offers insights into traffic flow patterns and potential bottlenecks, which can be crucial for identifying accident-prone areas and optimizing traffic management strategies. Chu et al. (2019) investigates the intricate relationship between traffic climate, driver behavior, and accident involvement in China. By analyzing these factors, the study aims to uncover underlying patterns and influences that contribute to traffic accidents, providing valuable insights for policymakers and traffic safety initiatives.

Guimarães and da Silva (2019) assess the effectiveness of regulations aimed at controlling alcohol consumption by drivers in the Federal District of Brazil. The study likely evaluates the impact of such regulations on reducing fatal traffic accidents, highlighting the importance of legal measures in promoting road safety. Nishitani (2019) explores the correlation between alcohol consumption and traffic accidents in Japan.

By examining this relationship, the study aims to shed light on the role of alcohol impairment in contributing to road traffic incidents, potentially informing targeted interventions and awareness campaigns. Mahata et al. (2019) conducts a spate-temporal analysis of the road traffic accidents in large Indian cities. Through this analysis, the study likely identifies spatial and temporal patterns of accidents, offering valuable insights for urban planning and traffic management strategies. Sheng et al. (2010) proposes a semantic event detection algorithm for traffic surveillance video based on a spate-velocity model.

This research likely focuses on leveraging video analytics techniques to detect and classify traffic events, including accidents, thereby enhancing the efficiency of traffic monitoring and management systems. Parsa et al. (2019) apply deep learning techniques to real-time traffic accident detection using spatiotemporal sequential data. By leveraging advanced machine learning algorithms, the study aims to develop more accurate and efficient

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ISSN: 0970-2555
Volume : 53, Issue 10, October : 2024

method for detecting and predicting traffic accidents, potentially leading to improved road safety measures. Additionally, studies by Joshua and Garber (1990) and Arvin et al. (2019)

Utilize regression models and connected vehicle message data to estimate accident rates and understand driving behavior at intersections, respectively.

These studies offer valuable insights into the statistical modeling of traffic accidents and the utilization of emerging technologies for enhancing traffic safety measures.

III. EXISTING METHODS:

Limited Integration of Intelligent Transportation Systems (ITS): The current system primarily relies on tangible infrastructure rather than fully leveraging Intelligent Transportation Systems (ITS). This limitation hinders the system's ability to take advantage of advanced technologies for efficient traffic management, including congestion and accident detection.

Reliance on External Devices: Many existing methods proposed for accident detection involve the use of external devices such as smartphones, VANET (Ad-hoc networks), GPS, GSM technologies, and mobile applications. This reliance on external devices introduces complexities and potential points of failure, increasing the system's overall vulnerability and reducing its reliability.

Unreliable Hardware, Particularly Sensors: One of the significant drawbacks of the current system is the unreliability of hardware components, particularly sensors. Malfunctions or inaccuracies in sensor readings can lead to false alarms or missed accident detections, compromising the effectiveness of the system in ensuring road safety.

Delays in Accident Alerts: The system experiences delays in sending accident alerts, primarily due to factors like the responsiveness of the GSM module. Delays in transmitting accident information can hinder emergency response efforts and exacerbate the consequences of accidents, increasing the risk of injuries and fatalities. Complexity and Maintenance: The complexity introduced by the integration of multiple devices and technologies in the current system adds to the maintenance burden.

Ensuring the proper functioning and synchronization of various components require ongoing monitoring and troubleshooting, consuming resources and time. Limited Scalability: The reliance on hardware-based solutions and external devices may limit the scalability of the current system. As traffic volumes increase or new areas require monitoring, scaling up the infrastructure to accommodate these changes becomes challenging and costly.

IV. PROPOSED SYSTEM

The proposed system introduces a novel approach to accident detection using video analysis.

Deep learning concepts, including Convolutional Neural Networks (CNN) with Long Short Term Memory (LSTM) units, are employed to train a model capable of accurately detecting accidents in videos. CNN offers shared-weights architecture and translation invariance, enhancing its ability to analyze visual data effectively.

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METHODOLOGY:

Data Collection: Gather a large dataset of accident images. These images may with and without accident images.

Data Preprocessing: Resize images to a uniform size suitable for CNN input. Normalize pixel values to a common scale.

Augment the dataset to increase its size and diversity. This can involve techniques like rotation, flipping, cropping.

Data Labeling: Each image is labeled according to its class (accident no accident).

Data Splitting: Divide the dataset into training, validation, and testing sets. A common split might be 80-25.

Model Architecture Selection: CNN sequential model architecture is used for image classification tasks.

Model Training: Initialize the chosen CNN architecture with random weights.
Train the model using the training dataset.
Utilize techniques like mini-batch gradient descent and back propagation for optimization. Monitor the model's performance on the validation set to prevent overfitting.

Model Evaluation: Evaluate the trained model's performance on the testing dataset. Metrics for evaluation can include accuracy, precision, recall, F1-score.

User Module: Using this module authorities or users who want to view live accident status with accident picture, location and see on map can login to application and view these detail

This module is used by ambulances, hospitals, police stations to reach location in short time.

System Module: Using this module system will load trained module and take live video form camera and convert to frames.

Send to model to predict accident or not and give beep sound and take snap shot and send to doctor and police station module to show on webpage and can find location on images from source to destination.

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ARCHITECTURE:

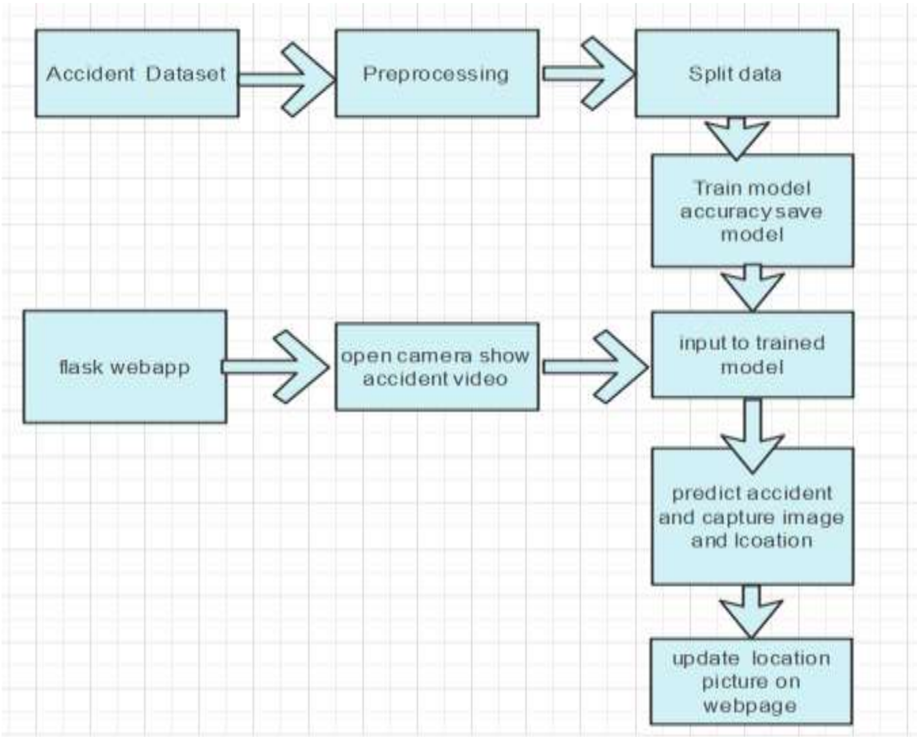

Figure 1: System Architecture

Figure 1 illustrates the framework of the proposed method ology representing data processing, classifiers, and a set of evaluation metrics employed in the approach. In the feature extraction process, the authors in extracted data points from the EEG signals. In our study, we considered those extracted data points as features and further preprocessed and normalized to ensure all the features are on a consistent scale, preventing certain features from dominating others in the learning process.

Further, the data was fed to the classifiers and evaluated with the following metrics. The three-tier software architecture emerged in the 1990s to overcome the limitations of the two-tier architecture. The third tier is between the user interface (client) and the data management (server) components.

This middle tier provides process management where business logic and rules are executed and can accommodate hundreds of users (as compared to only 100 users with the two tier architecture) by providing functions such as queuing, application execution, and database staging. The three tier architecture is used when an effective distributed client/server design is needed that provides increased performance, flexibility, maintainability, reusability, and scalability, while hiding the complexity of distributed processing from the user. These characteristics have made three layer architectures a popular choice for Internet applications and net-centric information systems.

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FLOW DIAGRAM:

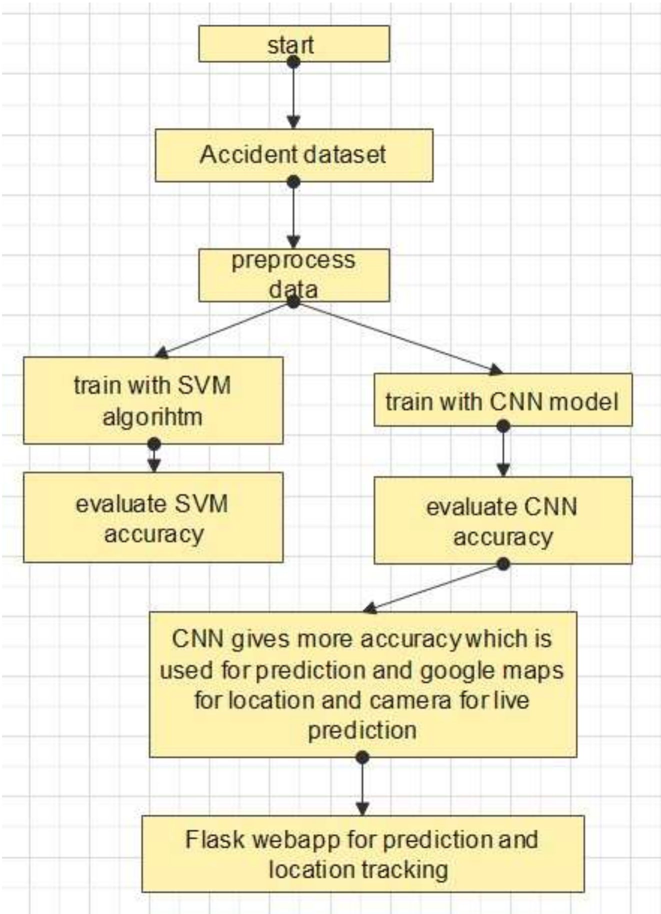
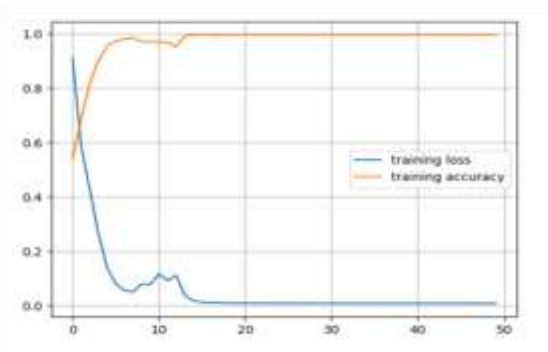
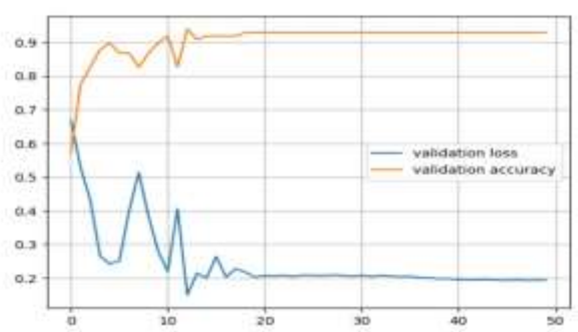


Figure 2: Model Flow Diagram

V. EVALUATION METRICS

Accuracy and Loss Graph





Above graph shows accuracy and loss graph for training and validation dataset in which training data has 98 percent accuracy where, as testing data has 97 accuracy.

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ISSN: 0970-2555
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RESULTS:

DATASET:

Home Page:

Registration Form:

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ISSN: 0970-2555
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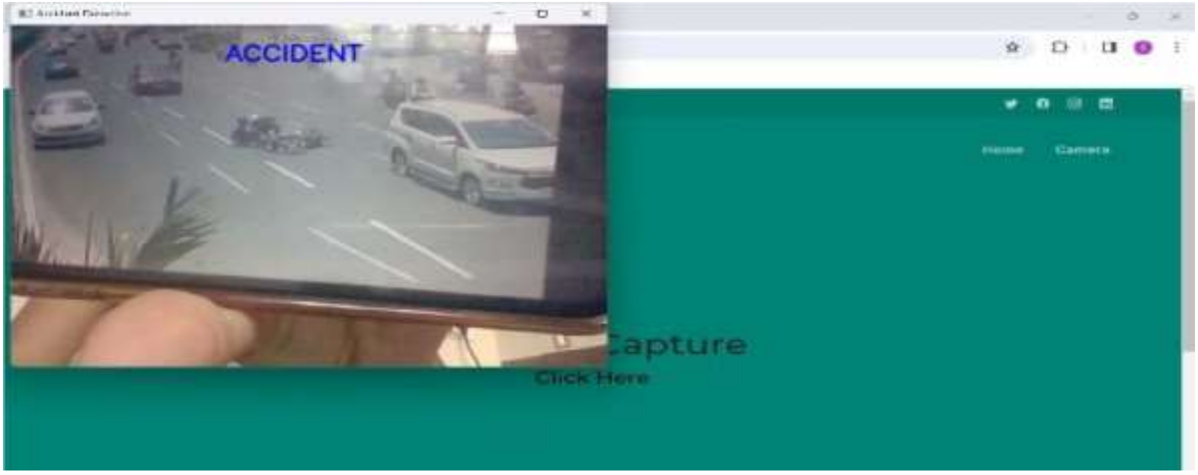
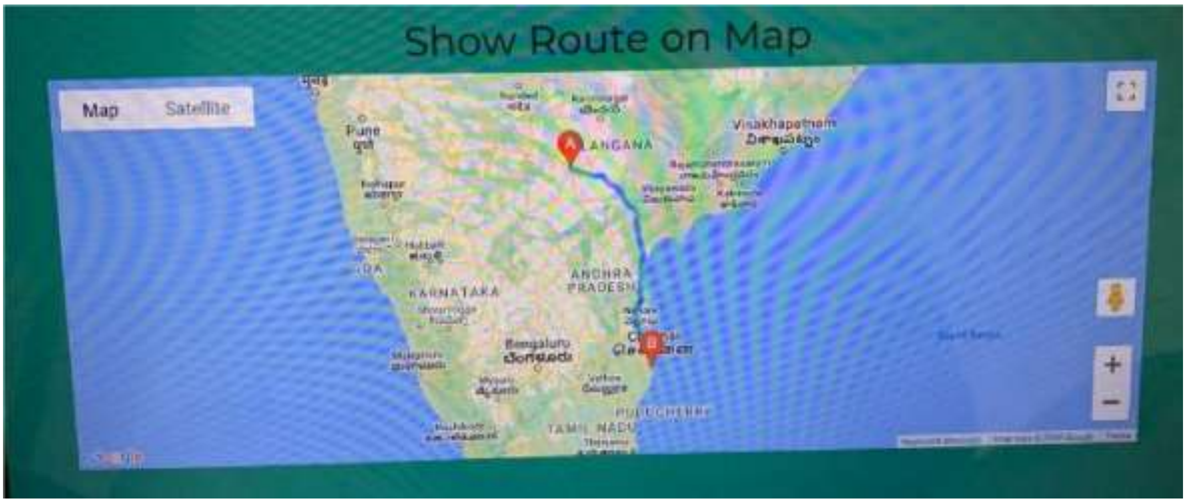
Prediction Result:



Location Page:



VI. CONCLUSION

The use of Convolutional Neural Networks (CNN) in accident detection systems provides a higher level of accuracy compared to traditional methods. By analyzing live images and sensor data, the system can more reliably identify accidents and reduce false positives, leading to more effective emergency response.

Integrating live image tracking with location sharing ensures that responders receive not just the location but also a visual context of the incident. This enables faster and more informed decision-making, potentially saving lives by allowing for a more precise and tailored response to each situation.

The combination of CNN-based image analysis, real-time tracking, and automated location sharing creates a comprehensive system for accident management. This integration addresses many gaps in existing systems, such as the lack of visual data and the need for immediate and accurate alerts to emergency services.

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VII. FUTURE SCOPE

The combination of CNN-based image analysis, real-time tracking, and automated location sharing creates a comprehensive system for accident management. This integration addresses many gaps in existing systems, such as the lack of visual data and the need for immediate and accurate alerts to emergency services.

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