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Deep Learning Approaches for Traffic Accident Detection

PETTUGADI SUNANDA
Post Graduate Student, M.C.A, Department of Information Technology ,University College of Engineering Science and Technology Hyderabad, Jawaharlal Nehru Technological University, Hyderabad, Telangana, India.
pettugadisunanda@gmail.com

ABSTRACT

Accident detection is a crucial component of intelligent transportation systems as it helps minimize emergency response delays and increases the likelihood of saving lives. This work introduces a deep learning framework based on Convolutional Neural Networks (CNNs) to identify road accidents from traffic surveillance footage. The model utilizes both RGB image frames and optical flow features to enhance detection accuracy, achieving a performance of nearly 87%. Once an accident is recognized, the system captures the incident frame, determines the location using Google Maps, and sends immediate alerts to nearby hospitals and police departments through cloud services. This real-time detection mechanism enables quicker emergency assistance, strengthens road safety, and supports the development of safer smart city infrastructures.

KEYWORDS

Convolutional Neural Networks (CNN),RGB Frames,Cloud ServicesOptical, Flow,Intelligent Transportation Systems.

INTRODUCTION

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.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.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.

LITERATURE REVIEW

- Early methods like Markov Models, Random Fields, and Sparse Reconstruction were used to detect unusual traffic events, giving good results.
- With deep learning, models such as Faster R-CNN, YOLO, and spatio-temporal analysis greatly improved accuracy, with many ranking high in AI City Challenges.
- Instead of heavy tracking methods, the proposed study focuses on background estimation and road segmentation with a decision-tree approach for faster and reliable anomaly detection.

METHODOLOGY

Model Architecture

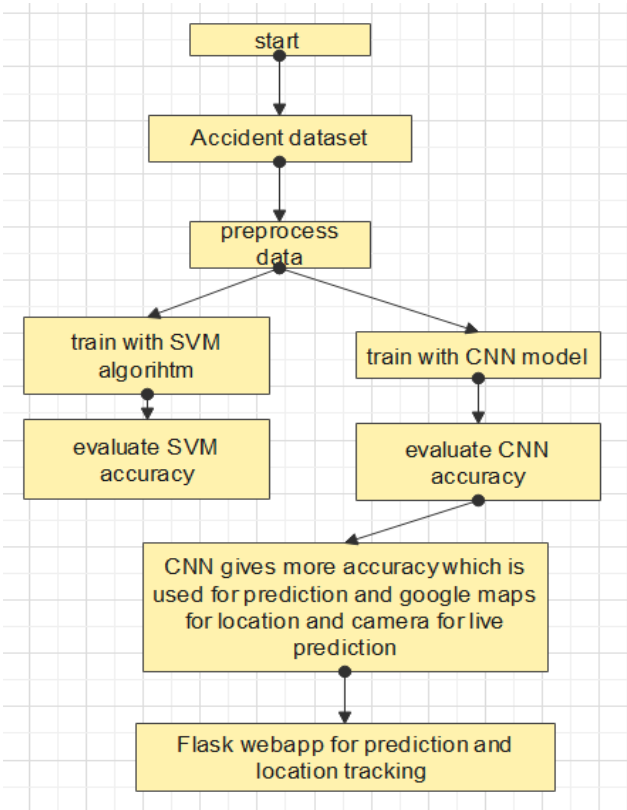


Fig. 1: System Architecture

Pre-processing Steps:

Data Collection: Source Identification,Keyword Selection,Automation,Validation and Standardization

Pre-processing: Continuous Frame Selection,Frame Skipping Strategy.

Accident Detection: Visual Feature Extraction,Model Adjustment,Training Experiments.

System Setup

- **Processor:** Intel® Core™ i3-7020U CPU @ 2.30GHz
- **Hard Disk:** 1 TB
- **Memory (RAM):** 4 GB
- **Input Devices:** Keyboard and Mouse
- **Operating System:** Windows XP / 7 / 10
- **Programming Language:** Python
- **Development Environment:** Anaconda
- **Library / Interface:** OpenCV

RESULTS

Unit Testing:

Sl #	Test Case	Items Tested	Sample Input	Expected Output	Actual Output	Remarks
UTC1	Load Dataset	Features and labels of dataset	Dataset CSV file	All features and labels should be displayed	Total data displayed	Pass
UTC2	Split Data	Dataset divided into train and test sets	Test/trai n size	Dataset split into two parts	Data divided based on test/train size	Pass

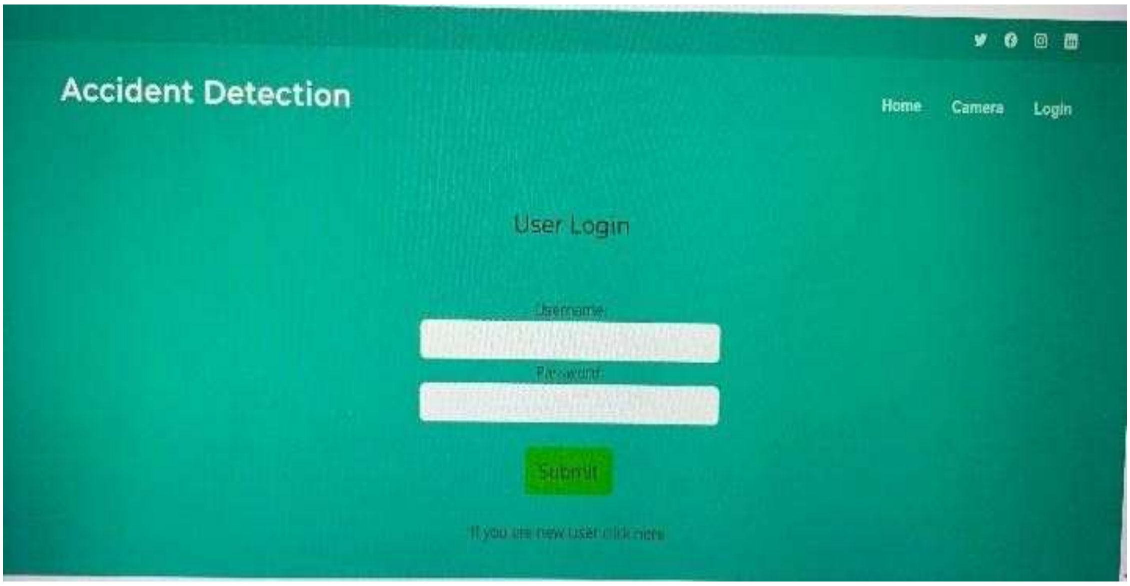
Sample Test Cases for Integration Testing:

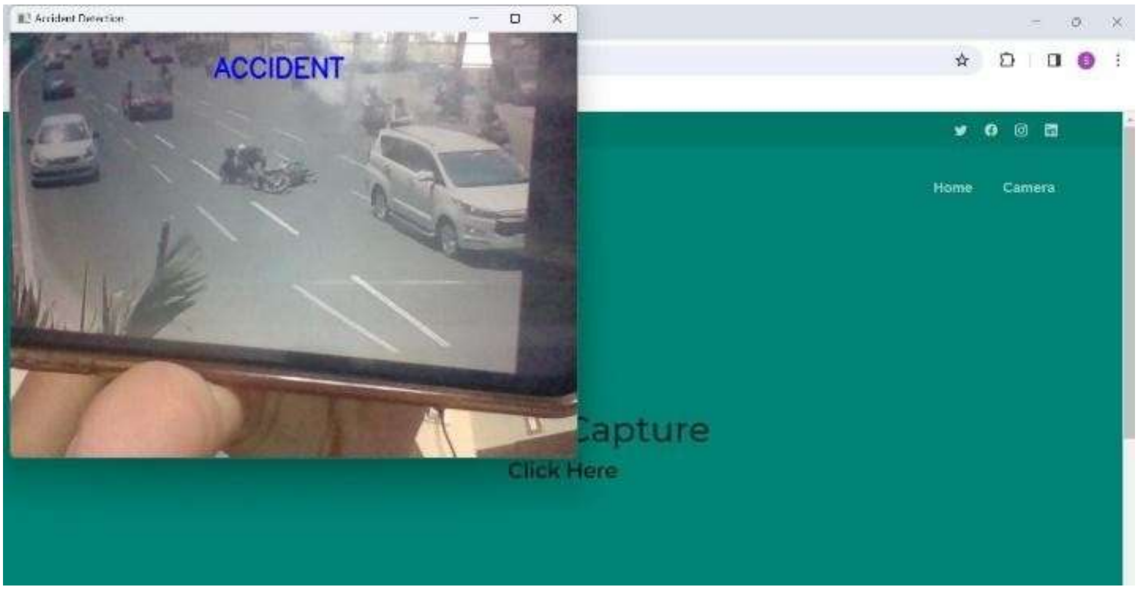
Sl #	Test Case	Items Tested	Sample Input	Expected Output	Actual Output	Remarks
ITC1	Train Model	Model fitting process	Training data (X and Y)	Model is fitted	Training completed, accuracy displayed	Pass
ITC2	Accura cy Calcul ation	Accuracy of algorithms	Test data (X and Y)	Accuracy metrics for each algorithm	Accuracy calculated for each model	Pass

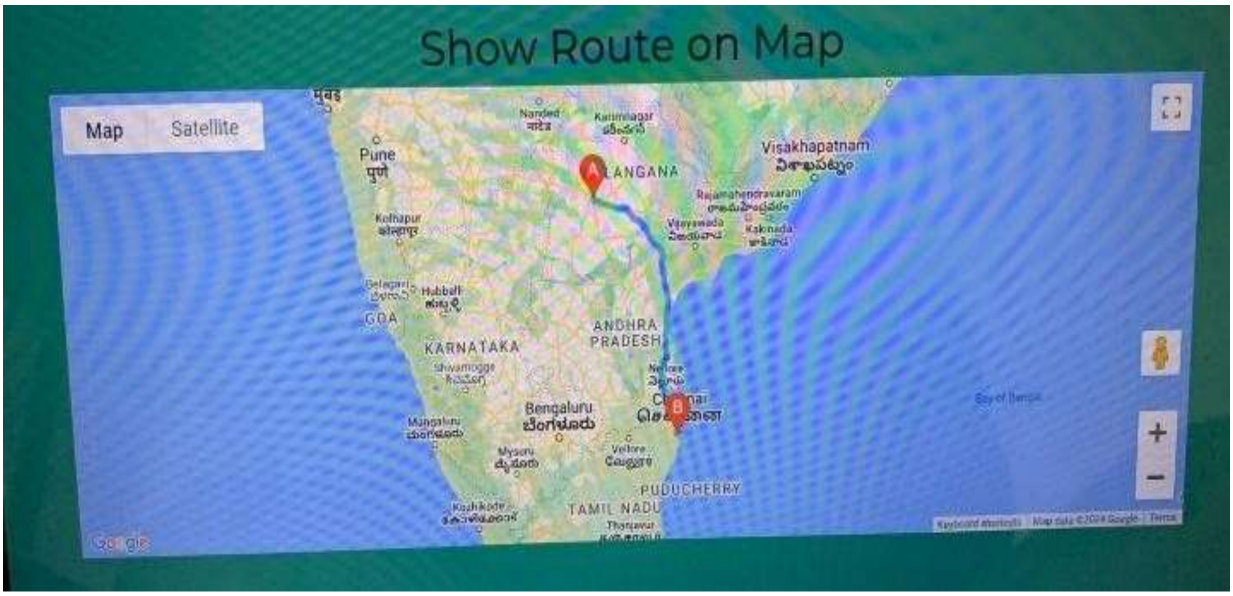
Sample Test Case for System Testing:

Sl #	Test Case	Items Tested	Sample Input	Expected Output	Actual Output	Remarks
STC1	System testing across different OS versions	Operating system compatibility	Execute the program on Windows XP / Windows 7 / Windows 8	Application performs optimally on Windows 7	Application performedas expected, with better performance on Windows 7	Pass

OUTPUT SCREENS


Accident Detection
Home
Camera
Login
User Login
Submit


ACCIDENT
Home
Camera
Capture
Click Here


Show Route on Map
Map
Satellite
Pune
Visakhapatnam
ANDHRA PRADESH
KARNATAKA
Bengaluru
PUDUCHERRY
TAMIL NADU

CONCLUSION

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.

REFERENCES

1. Li, M.Z. The Road Traffic Analysis Based on an Urban Traffic Model of the Circular Working Field. Acta Math. Appl. Sin. 2004, 20, 77–84. [CrossRef]
2. Chu, W.; Wu, C.; Atombo, C.; Zhang, H.; Özkan, T. Traffic Climate, DriverBehaviour, and Accidents Involvement in China. Accid. Anal. Prev. 2019, 122, 119– 126. [CrossRef]
3. Guimarães, A.G.; da Silva, A.R. Impact of Regulations to Control Alcohol Consumption by Drivers:An Assessment of Reduction in Fatal Traffic Accident Numbers in the Federal District, Brazil. Accid. Anal. Prev. 2019, 127, 110–117. [CrossRef] [PubMed]
4. Nishitani, Y. Alcohol and Traffic Accidents in Japan. IATSS Res. 2019, 43, 79–83. [CrossRef]
5. Mahata, D.; Narzary, P.K.; Govil, D. Spatio-Temporal Analysis of Road Traffic Accidents in Indian Large Cities. Clin. Epidemiol. Glob. Health 2019, 7, 586–591. [CrossRef]
6. Sheng, H.; Zhao, H.; Huang, J.; Li, N. A Spatio-Velocity Model Based Semantic Event Detection Algorithm for Traffic Surveillance Video. Sci. China Technol. Sci. 2010, 53, 120–125. [CrossRef]
7. Parsa, A.B.; Chauhan, R.S.; Taghipour, H.; Derrible, S.; Mohammadian, A. Applying Deep Learning to Detect Traffic Accidents in Real Time Using Spatiotemporal Sequential Data. arXiv 2019, arXiv:1912.06991.