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Original Article

Deep Learning Models for Traffic Accident Prediction

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Abstract

Road traffic accidents are a major global safety concern, resulting in significant loss of life and economic damage each year. Traditional accident prediction approaches rely on statistical and rule-based models, which struggle to capture complex non-linear relationships among traffic, environmental, and human behavioural factors. Recent advancements in deep learning offer powerful tools for modelling such complex patterns using large-scale traffic data. This research paper explores deep learning-based approaches for traffic accident prediction, including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and hybrid models. The paper discusses data sources, feature extraction, model architectures, performance evaluation metrics, challenges, and future research directions. Experimental results reported in existing studies demonstrate that deep learning models significantly outperform traditional machine learning techniques in predicting traffic accidents, enabling proactive road safety management.

Keywords: *Traffic Accident Prediction, Deep Learning, LSTM, CNN, Intelligent Transportation Systems, Road Safety*

Introduction

Traffic accidents are one of the leading causes of death worldwide, especially in developing countries. According to global road safety reports, millions of people are injured or killed annually due to traffic-related incidents. Accurate accident prediction is essential for improving road safety, optimizing traffic management, and supporting intelligent transportation systems (ITS).

Traditional accident prediction methods such as regression analysis and decision trees depend heavily on manual feature engineering and linear assumptions. These methods are insufficient for modelling the complex interactions among traffic flow, weather conditions, road geometry, and driver behaviour.

Deep learning models have emerged as a promising solution due to their ability to automatically learn hierarchical features from large and heterogeneous datasets. This paper investigates deep learning techniques for predicting traffic accidents and highlights their advantages over conventional methods.

Predicting where and when a traffic accident will occur is a "needle in a haystack" problem. Accident data is inherently **sparse**—most road segments have zero accidents at any given time. However, deep learning models excel at extracting features from high-dimensional data, such as real-time GPS trajectories, weather sensors, and road geometry. The goal of modern research is to transition from reactive management to **proactive intervention** using predictive analytics.

Related Work

Early traffic accident prediction studies primarily used statistical methods such as Poisson regression and logistic regression. With the growth of data availability, machine learning models such as Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbours (k-NN) were introduced.

Recent research has shifted toward deep learning models:

- **CNN-based models** have been used to extract spatial features from traffic maps.
- **RNN and LSTM models** effectively capture temporal dependencies in traffic flow data.
- **Hybrid CNN–LSTM architectures** combine spatial and temporal modelling for improved accuracy.

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Studies consistently report higher prediction accuracy, recall, and robustness using deep learning models compared to traditional approaches.

Data Sources and Feature Description

Data Sources

The performance of deep learning models for traffic accident prediction heavily depends on the quality, diversity, and scale of input data. Traffic accidents are influenced by multiple dynamic and static factors; therefore, data are typically collected from various sources to capture the complex interactions within traffic systems. The primary data sources used in traffic accident prediction are described below.

1. **Traffic Data**
   Traffic data provide real-time and historical information about road usage and driving conditions. This includes vehicle speed, traffic volume, occupancy rate, and congestion levels. Such data are commonly collected using loop detectors, traffic cameras, GPS devices, and mobile applications. Traffic data help identify abnormal traffic patterns, such as sudden congestion or speed fluctuations, which are often associated with higher accident risk.
2. **Accident Records**
   Historical traffic accident data form the core dataset for prediction tasks. These records typically include information such as accident location, time, severity, number of vehicles involved, and causes of the accident. Accident records are usually obtained from traffic police departments, transportation agencies, or open government databases. These data enable models to learn recurring accident patterns and identify high-risk locations and time periods.
3. **Weather Data**
   Weather conditions have a significant impact on driving behavior and road safety. Weather data include variables such as rainfall, fog, temperature, humidity, wind speed, and visibility. These data are collected from meteorological stations or online weather services. Adverse weather conditions often reduce road friction and visibility, increasing the probability of accidents.
4. **Road Network and Infrastructure Data**
   Road network data describe the physical characteristics of transportation infrastructure, including road type, number of lanes, intersections, curvature, slope, traffic signals, and speed limits. Geographic Information Systems (GIS) are commonly used to represent road network information. These static features help deep learning models understand how road design and layout contribute to accident occurrence.
5. **Temporal and Calendar Data**
   Temporal factors such as time of day, day of week, weekends, holidays, and seasonal variations play an important role in accident prediction. For example, accident rates are typically higher during peak hours and adverse seasonal conditions. These features are derived from timestamps associated with traffic and accident data.
6. **Socioeconomic and Event Data**
   Additional contextual data, such as population density, land use, nearby commercial areas, construction activities, and major public events, can also influence traffic accident risk. These data are often obtained from census records, urban planning databases, and event schedules. Incorporating such information helps improve prediction accuracy, especially in urban environments.

Features Used

Common features include:

- Traffic volume and speed
- Vehicle density
- Time of day and day of week
- Weather conditions (rain, fog, visibility)
- Road characteristics (lane count, curvature)
- Accident history of the location

Deep Learning Models for Accident Prediction

- **Convolutional Neural Networks (CNN)**
  CNNs are used to capture spatial patterns in traffic data. Traffic flow data can be represented as grid maps where CNN layers extract spatial correlations between neighboring road segments.
- **Recurrent Neural Networks (RNN)**
  RNNs process sequential data and are suitable for time-series traffic data. However, standard RNNs suffer from vanishing gradient problems.
- **Long Short-Term Memory (LSTM) Networks**
  LSTM networks overcome RNN limitations by introducing memory cells and gating mechanisms. LSTMs effectively capture long-term temporal dependencies and are widely used for traffic accident prediction.
- **Hybrid CNN–LSTM Models**
  Hybrid models combine CNNs for spatial feature extraction and LSTMs for temporal modeling. These models show superior performance in predicting accidents across urban and highway environments.

Methodology

Data Preprocessing

- Handling missing values
- Data normalization
- Time-window segmentation
- Labeling accident and non-accident events

Model Training

The dataset is divided into training, validation, and testing sets. Models are trained using backpropagation with optimizers such as Adam or RMSprop.

Evaluation Metrics

Model performance is evaluated using:

- Accuracy
- Precision
- Recall
- F1-score
- Area Under the ROC Curve (AUC)

Results and Discussion

Experimental studies indicate that deep learning models significantly outperform traditional machine learning approaches. LSTM and CNN–LSTM models achieve higher recall, which is critical for accident prediction systems where missing an accident event can have severe consequences.

The results also show that incorporating weather and temporal features improves prediction performance. However, model interpretability remains a challenge.

Recent studies (2024–2026) show that hybrid **Spatio-Temporal Graph Neural Networks (ST-GNN)** consistently outperform traditional models by **15–25%**. Specifically, the inclusion of "Attention Mechanisms" allows the model to "focus" on specific external triggers, such as a sudden drop in visibility due to fog, which traditional models might overlook when averaged over time.

Challenges and Limitations

Despite their effectiveness, deep learning-based accident prediction systems face several challenges:

- Data imbalance between accident and non-accident cases
- High computational requirements
- Lack of labeled data in some regions
- Limited model interpretability
- Privacy concerns related to traffic data collection

Applications

- Real-time traffic risk warning systems
- Smart traffic signal control
- Accident hotspot identification
- Emergency response optimization
- Autonomous vehicle decision support

Future Research Directions

Future research can focus on:

- Explainable AI for accident prediction
- Federated learning for privacy-preserving data sharing
- Integration with vehicle-to-everything (V2X) communication
- Transfer learning for cross-city accident prediction
- Multimodal data fusion using video, sensor, and textual data

Conclusion

Deep learning models provide a powerful framework for traffic accident prediction by effectively capturing complex spatial and temporal patterns in traffic data. CNN, LSTM, and hybrid architectures demonstrate superior performance over traditional models, enabling proactive road safety measures. Continued advancements in data availability, model interpretability, and real-time deployment will further enhance the effectiveness of intelligent road safety systems.

Deep Learning has transformed traffic safety from a statistical guessing game into a high-precision science. High risk due to combined effect of wet road and high speed. Furthermore, the integration of Large Language Models (LLMs) to process text-based police reports is the next frontier in semantic feature extraction.

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Conflicts of interest
The authors declare that there are no conflicts of interest regarding the publication of this paper

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