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AI-Based Traffic Accident Risk Prediction a Deep Learning Approach Using CNN-LSTM Hybrid Architecture

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Abstract: Traffic accidents remain a critical public safety challenge worldwide, causing millions of fatalities and economic losses annually. This paper presents an AI-driven framework for real-time traffic accident risk prediction using a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) architecture. The proposed system integrates heterogeneous data sources including environmental conditions, road geometry, traffic flow parameters, and historical accident records to generate spatio temporal risk scores. Feature engineering techniques combined with attention mechanisms enable the model to capture both local spatial patterns and long-range temporal dependencies. Experimental evaluation on a large-scale dataset comprising over 1.2 million accident records across five years demonstrates that the proposed model achieves 94.8% accuracy, outperforming standalone CNN, LSTM, Random Forest, and Gradient Boosting baselines. The system outputs a real-time risk heat map and provides interpretable alerts, enabling proactive traffic management. This work contributes a scalable, deployable pipeline for smart city traffic safety infrastructure.
Keywords: Traffic accident prediction, deep learning, CNN-LSTM, spatiotemporal analysis, risk assessment, intelligent transportation systems, smart city.

I. INTRODUCTION

Road traffic accidents constitute one of the leading causes of mortality and morbidity globally. According to the World Health Organization (WHO), approximately 1.35 million people die each year as a result of road traffic crashes, and between 20 and 50 million suffer non-fatal injuries. The economic burden of road accidents on nations, especially developing countries, is estimated to be 3% of their annual Gross Domestic Product (GDP). Despite advances in vehicle safety technology and road infrastructure, accident rates continue to rise in densely populated urban environments. Traditional approaches to accident prevention have relied on static risk assessments, manual traffic surveys, and reactive post-accident analysis. These methods lack the ability to provide real-time, proactive warnings based on dynamic environmental and traffic conditions. The advent of Artificial Intelligence (AI), particularly deep learning, has opened transformative opportunities for predictive traffic safety systems capable of analyzing large-scale, multi- modal data streams in real time. This paper proposes an AI-based traffic accident risk prediction system that harnesses the complementary strengths of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks in unified hybrid architecture. CNNs excel at extracting localized spatial features from road and environmental inputs, while LSTM networks are effective at modeling sequential temporal patterns in traffic flow and historical accident data. Together, they enable a robust spatio temporal understanding of accident risk.

A. Motivation

The primary motivation for this research is the gap between the volume of available traffic data and the limited use of advanced AI techniques in operational safety systems. Modern cities generate vast amounts of real-time sensor data from IoT-enabled road sensors, GPS trajectories, weather APIs, and CCTV cameras yet this data remains underutilized for predictive safety applications. By leveraging this data through intelligent models, it becomes possible to predict high-risk periods and locations before accidents occur.

B. Objectives

- Design a multi-modal data fusion pipeline integrating weather, road, traffic, and historical data.
- Develop a CNN-LSTM hybrid model for spatiotemporal accident risk prediction.
- Implement an attention mechanism to improve feature relevance weighting.
- Evaluate the model on real-world accident datasets with established metrics.
- Deploy a real-time risk visualization dashboard for practical usability.

LITERATUREREVIEW

A substantial body of research has explored machine learning and statistical methods for traffic accident prediction. Early studies employed logistic regression and negative binomial regression to model accident frequency using road geometry and traffic volume as predictors [1]. While these statistical models provided initial insights, they were limited in their ability to handle high-dimensional, non-linear data. Support Vector Machines (SVM) and decision tree-based methods, including Random Forests and Gradient Boosting, demonstrated improved performance by capturing non- linear feature interactions [2]. Mohamed et al. [3] applied Random Forest classifiers on the UK STATS19 accident dataset and reported 84.2% classification accuracy. However, these methods require extensive manual feature engineering and do not naturally model temporal dynamics. Recurrent Neural Networks (RNNs), especially LSTM architectures, have been applied to sequential traffic prediction tasks. Zhao et al. [4] used LSTM to predict accident occurrence probability using time-series speed data and achieved superior performance over traditional methods. Chen and Wang [5] proposed a deep neural network (DNN) incorporating historical accident data and weather indices, reporting significant improvements in F1-score. More recent studies have focused on spatial–temporal fusion. Tang et al. [6] combined graph convolutional networks (GCN) with LSTM to capture road network topology and temporal sequences simultaneously. Baoetal. [7] applied attention-based transformers to multi-source traffic data, demonstrating that attention mechanisms effectively highlight critical features for accident risk. However, most existing systems lack real-time data integration and practical deployment pipelines, which the current work addresses.

PROPOSED METHODOLOGY

The proposed system architecture consists of four principal modules: (1) Multi-Source Data Collection and Fusion, (2) Preprocessing and Feature Engineering, (3) CNN-LSTM Hybrid Model with Attention, and (4)Risk Score Generation and Visualization.Figure1 illustrates the end-to- end architecture of the proposed framework.

C. System Architecture Overview

The pipeline begins with raw data ingestion from heterogeneous sources, followed by preprocessing and normalization. Engineered features are fed into the CNN module, which extracts spatial representations. These representations, along with sequential time-series features, are passed to the LSTM module. An additive attention layer computes importance weights over temporal hidden states. The final dense layers output a continuous risk score between 0 (low risk) and 1 (critical risk), which is thresholded into three alert classes: Low, Medium, andHigh.

D. Data Collection and Feature Engineering

The dataset comprises records from the National Highway Traffic Safety Administration (NHTSA), complemented by real-time weather data from the OpenWeatherMap API and road geometry data extracted from OpenStreetMap. The dataset spans five years (2018–2022) and contains over 1.2 million labelled accident and non-accident instances.

Table I: Dataset Features and Sources

Feature Category	Features Used	Source	Coverage
Environmental	Weather, Temperature, Visibility, Precipitation	IoT Sensors / APIs	Real-time
Road Geometry	Road Type, Curve, Gradient, Lane Count, Junction	GIS/ Open Street Map	National
Traffic Flow	Speed, Volume, Congestion Index, Headway	Traffic Cameras	Urban Areas
Temporal	Time of Day, Day of Week, Season, Public Holidays	System Timestamp	Historical
Historical Acc.	Accident Count, Severity, Location, Cause	NHTSA/Police Data	10 Years

Missing values are handled through median imputation for continuous features and mode imputation for categorical features. Class imbalance (accident vs. non-accident ratio ≈ 1:12) is addressed using Synthetic Minority Over-sampling Technique (SMOTE) combined with random under-sampling. The prefix "non"is not a word; it should be joined to the word it modifies, usually without a hyphen. There is no period after the "et" in the Latin abbreviation "et al.". The abbreviation "i.e." means "that is", and the abbreviation "e.g." means "for example". An excellent style manual for science writers is[7].

E. CNN-LSTM Hybrid Architecture

The spatial feature extractor consists of three 1D convolutional layers with kernel sizes 3, 5, and 7, respectively, each followed by Batch Normalization and ReLU activation. Max pooling with stride 2 is applied after each convolutional block. This hierarchical structure captures multi-scale spatial patterns within road segments. The temporal modeling module employs a two-layer bidirectional LSTM with hidden size 256. Bidirectionality enables the model to capture both past and future contextual dependencies in time-series traffic data. Drop out with rate 0.3 is applied between LSTM layers to regularize the model and reduce over fitting. The attention mechanism assigns a scalar weight αt to each LSTM hidden state ht via the Bahdanau additive attention formulation: $et=v^{T}\tanh(W_1ht+b_1),\alpha t=\exp(et)/\Sigma\exp(ek),c=\Sigma\alpha tht$ where v, W□, and b□ are learnable parameters, and c is the context vector fed into the classification head. This mechanism enables the model to focus on temporally critical windows preceding accident occurrence.

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F. Training Configuration

1. Optimizer: A dam with learning rate 0.001and weight decay1×10^{-4}
2. Loss Function: Binary Cross-Entropy with label smoothing(ε=0.1)
3. BatchSize: 256; Epochs:80 with early stopping (patience=10)
4. Train/Validation/TestSplit:70%/15%/15%
5. Hardware:NVIDIATeslaT4GPU,16GBVRAM

EXPERIMENTAL RESULTS AND DISCUSSION

This section presents a comprehensive evaluation of the proposed CNN-LSTM model against established baselines. All experiments were conducted using PyTorch 2.0 with CUDA 11.8. Performance was measured using Accuracy, Precision,Recall,F1-Score,andAreaUndertheROCCurve (AUC-ROC).

G. Comparative Performance

As shown in Table II, the proposed Hybrid CNN-LSTM model achieves the highest performance across all metrics, attaining an accuracy of 94.8% and an F1-score of 94.2%. The Gradient Boosting model delivers competitive results (91.2% accuracy) but lacks temporal modeling capabilities. The standalone CNN model benefits from spatial feature extraction yet falls short in capturing temporal sequences, confirming the necessity of the LSTM component. The bidirectional LSTM with attention further improves upon the standard LSTM by leveraging future context and selectively weighting informative time steps.

Table II: Model Performance Comparison

Model	Accuracy	Precision	Recall	F1- Score
Logistic Regression	79.3%	77.1%	76.5%	76.8%
Random Forest	88.7%	87.4%	88.1%	87.7%
Gradient Boosting	91.2%	90.6%	91.0%	90.8%
CNN (Spatial)	92.5%	91.8%	92.3%	92.0%
Hybrid CNN- LSTM	94.8%	93.9%	94.5%	94.2%

H. Ablation Study

An ablation study was conducted to evaluate the contribution of individual components. Removing the attention mechanism reduced accuracy by 1.9% (from94.8% to 92.9%). Eliminating bidirectionality in the LSTM further reduced accuracy to 91.4%. Replacing the multi- layer CNN with a single convolutional layer decreased accuracy to 90.7%. These results confirm that each architectural component contributes meaningfully to overall performance.

I. Real-Time Risk Visualization

The trained model was integrated into a real-time dashboard using Flask and Folium. Road segments are color-coded based on predicted risk: green (< 0.3), orange (0.3–0.65), and red (> 0.65). The system processes incoming sensor data streams via Apache Kafka, achieving an average inference latency of 38 ms per segment, suitable for operational deployment in smart city traffic management centers.

CONCLUSION AND FUTURE WORK

This paper presented an AI-based traffic accident risk prediction system leveraging a CNN-LSTM hybrid model augmented with an additive attention mechanism. The system integrates multi-source heterogeneous data and produces real-time risk scores with high accuracy (94.8%). The proposed framework addresses key limitations of prior work, including lack of real-time integration, limited temporal modeling, and absence of interpretable outputs. The comparative evaluation demonstrated that the hybrid architecture consistently outperforms traditional machine learning models and single-modality deep learning approaches. The real-time deployment pipeline achieves low inference latency, validating the system's practical feasibility for smart city applications. Future work will explore: (1) integration of vision-based features from roadside CCTV cameras using 3D-CNN, (2) graph neural network extensions to model road network topology, (3) federated learning for privacy-preserving model training across multiple city datasets, and (4) extension to multi-class severity prediction (property damage, injury, fatal).

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