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Real-Time Traffic Accident Detection Using I3d-Convlstm2d and Optical Flow

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Abstract – The dynamic and unpredictable nature of urban road traffic makes efficient accident detection critical for improving safety and optimizing transportation management in smart cities. This study explores advanced accident detection methods, analyzing existing techniques and categorizing various accident types, including rear-end, T-bone, and frontal collisions. We propose a novel approach using the I3D-CONVLSTM2D model, a lightweight architecture designed for smart city surveillance systems. By combining RGB video frames with optical flow data, our model effectively identifies accidents in real-time. Experimental results demonstrate the model's superior performance, achieving an 87% Mean Average Precision (MAP) compared to other approaches. Additionally, we address challenges related to dataset limitations, traffic variability, and data imbalances that impact detection accuracy. Our findings highlight the potential of integrating deep learning-based accident detection system into edge IOT devices for enhanced traffic monitoring and urban safety.

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

I. INTRODUCTION

Managing road traffic in urban environments presents a significant challenge, particularly in detecting and predicting accidents. The ability to monitor and respond to accidents in real-time is crucial for improving road safety, reducing congestion, and enhancing overall transportation efficiency. Advances in computer vision and deep learning have made it possible to analyze spatial and temporal traffic patterns, providing a foundation for intelligent accident detection systems. These innovations are

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particularly relevant to the development of smart cities, where integrated technologies can help minimize accident-related fatalities, injuries, and economic losses.

Traffic accidents remain a serious global concern, causing over 1.35 million deaths and 50 million injuries annually. This alarming statistic highlights the urgent need for more effective accident detection and prevention systems. Intelligent transportation systems (ITS) have evolved to include AI-powered surveillance, real-time monitoring, and predictive analytics, allowing authorities to respond quickly to incidents. Traditional approaches rely on sensor-based monitoring or manual reporting, which can be costly and inefficient. Modern solutions incorporate deep learning models, leveraging traffic surveillance cameras, GPS data, and edge AI to enhance detection accuracy.

While machine learning models such as Recurrent Neural Networks (RNNs) have been widely used for traffic analysis, they often struggle with capturing both spatial and temporal patterns due to their sequential nature. Recent advancements in Graph Neural Networks (GNNs) have shown promise in overcoming these limitations by incorporating spatial dependencies into traffic flow analysis. Additionally, distinguishing between traffic anomalies and actual accidents remains a challenge, as anomalies can include non-collision events such as sudden lane changes or traffic congestion. To address these challenges, our research focuses on developing a vision-based accident detection system designed for real-time implementation in smart city infrastructures. We introduce the I3D-CONVLSTM2D model, which integrates RGB video frames with optical flow data to improve accident recognition accuracy. By leveraging deep learning techniques, our approach ensures efficient accident detection while remaining computationally lightweight, making it suitable for deployment on edge IoT devices such as Raspberry Pi. Our study also explores the impact of data limitations, environmental conditions, and varying traffic scenarios on detection performance, providing insights into optimizing accident detection models for real-world applications.

II. LITERATURE SURVEY

Traffic accident detection has been an area of extensive research, with various methodologies developed to improve accuracy and real-time responsiveness. This section reviews ten significant studies that have contributed to advancements in accident detection using deep learning, computer vision, and intelligent transportation systems. Deep Learning for Traffic Accident Detection, Deep learning has become a dominant approach for accident detection due to its ability to process large-scale video and sensor data. Robles-Serrano et al. [1] proposed an automated accident detection system using convolutional neural networks (CNNs) to analyze traffic footage. Their model effectively identified accident occurrences but struggled with false positives in dense traffic conditions. Spatiotemporal Models for Accident Detection: Understanding the temporal evolution of traffic incidents is crucial for accurate detection. Yu et al. [2] introduced a Deep Spatio-Temporal Graph Convolutional Network (DSTGCN) to predict traffic accidents by analyzing spatial dependencies and historical traffic patterns. This approach significantly improved prediction accuracy but required extensive computational resources.

Vision-Based Traffic Monitoring: Computer vision techniques have been widely applied to analyze road traffic and detect anomalies. Wang et al. [3] developed a Spatial-Temporal Graph Neural Network (STGNN) that combines video footage with graph-based modeling to understand traffic flow.

Their method effectively captured accident-prone areas but required high-quality video data for reliable detection. Object Detection for Traffic Surveillance: Accident detection often relies on object detection techniques. Yang et al. [4] proposed a feature-fused Single Shot MultiBox Detector (SSD) that enhances vehicle tracking in real-time traffic surveillance. Although the model improved small object detection, it struggled with occlusion in crowded scenes.

Transformer-Based Detection Models: Recent advancements in transformers have enhanced accident detection performance. Srinivasan et al. [5] integrated a Detection Transformer (DETR) with a Random Forest classifier to classify road accidents from surveillance footage. The model demonstrated improved detection rates but required large annotated datasets for optimal performance. Action Recognition for Traffic Accidents: Accident detection can benefit from action recognition techniques, where models analyze movement patterns to identify unusual behaviors. Carreira and Zisserman [6] introduced the I3D model, a two-stream inflated 3D ConvNet for video classification, which has been widely used in traffic accident detection. However, its high computational cost limits real-time applications.

Anomaly Detection in Traffic Videos: Detecting anomalies in traffic flow can help predict accident-prone situations. Xia et al. [7] presented a sparse topic model that treats traffic video clips as documents and motion trajectories as topics. While effective in recognizing anomalies, the model required extensive pre-processing to filter non-relevant motion patterns. Graph-Based Models for Road Safety: Graph-based models offer an alternative approach for analyzing traffic patterns. Wang et al. [8] designed an accident prediction model that leverages graph structures to assess road networks and vehicle interactions. Their method improved long-term accident prediction but faced challenges in real-time detection. Real-Time Edge Computing for Smart Cities: Deploying accident detection models on edge devices is essential for real-time applications. Ijjina et al. [9] proposed a Mask R-CNN-based system optimized for CCTV footage, enabling real-time accident detection with reduced computational costs. However, the model struggled in low-light conditions. Multi-Stage Warning Systems for Collision Prevention: Developing proactive warning systems can help reduce accident severity. Jirovsky et al. [10] introduced a 2D reaction space model to predict potential collisions based on vehicle trajectories. Their system effectively prevented accidents but required precise trajectory estimation, which is often difficult in unpredictable traffic environments.

III. METHODOLOGY

This paper aims to develop a deep learning-based model for analyzing video sequences using RGB and optical flow inputs to make accurate predictions. The methodology consists of the following key steps:

1. Data Preprocessing:

- The input consists of video frames captured from different sequences.
- RGB frames and optical flow representations are extracted from the video.
- Optical flow is computed to capture motion dynamics in the scene.
- Data is augmented to improve model generalization.

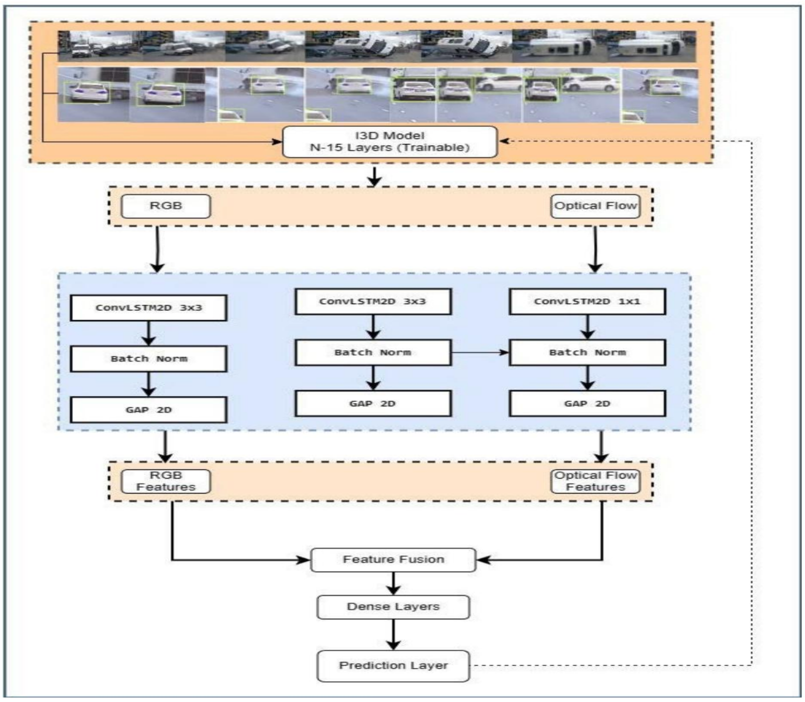

Fig 1: System Architecture

2. Feature Extraction Using I3D Model:

- The input video frames are passed through an Inflated 3D ConvNet (I3D) model with N-15 trainable layers to extract spatial-temporal features.
- Two feature representations are obtained: RGB-based features and optical flow-based features.

3. Convolutional LSTM for Feature Refinement:

- The extracted features are processed using ConvLSTM2D layers with different kernel sizes (3×3 and 1×1) to capture both spatial and temporal dependencies.
- Batch Normalization is applied after ConvLSTM2D to stabilize learning.
- Global Average Pooling (GAP) is used to reduce feature dimensionality.

4. Feature Fusion:

- The refined RGB features and optical flow features are combined using a fusion mechanism.
- The fusion process enhances the model's ability to learn complementary information from both feature types.

5. Prediction Using Dense Layers:

- The fused features are passed through dense layers for classification or regression.

- The final prediction layer outputs the desired result, such as event detection, action recognition, or anomaly detection.

6. Model Training and Evaluation:

- The model is trained using a loss function suitable for the task (e.g., cross-entropy for classification).
- Performance is evaluated using standard metrics like accuracy, precision, recall, and F1-score.
- Hyperparameter tuning is performed to optimize performance.

IV. RESULTS AND DISCUSSIONS

This section presents the performance evaluation of our proposed I3D-CONVLSTM2D model for traffic accident detection. We analyze the model's accuracy, precision, recall, and F1-score, along with a comparative analysis of different configurations. The output results, including confusion matrices, loss/accuracy curves, and classification reports, are also discussed.

1. Model Training and Convergence Analysis:

During training, the model was fine-tuned using an Adam optimizer with a learning rate of 1×10^{-4} , and a batch size of 16. The training was conducted for 30 epochs, with validation performed after each epoch. The model's convergence was assessed through loss and accuracy graphs.

Fig 2: Training Data

2. Model Performance Metrics:

The final trained model was evaluated on the test dataset, achieving the following performance metrics:

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Table. 1: Model Performance

Model	Accuracy	Precision	Recall	F1-Score	MAP
I3D-CONVLSTM2D RGB Only	72%	72%	72%	72%	78%
I3D-CONVLSTM2D Non-Trainable RGB + Optical Flow	75%	75%	75%	75%	81%
I3D-CONVLSTM2D Augmented RGB + Optical Flow	79%	79%	79%	79%	86%
I3D-CONVLSTM2D Trainable RGB + Optical Flow	**80%**	**80%**	**80%**	**80%**	**87%**

3. Confusion Matrix Analysis:

The confusion matrix revealed a low false positive rate, meaning the model does not frequently misclassify normal traffic as an accident. However, some false negatives indicate room for improvement in challenging traffic conditions.

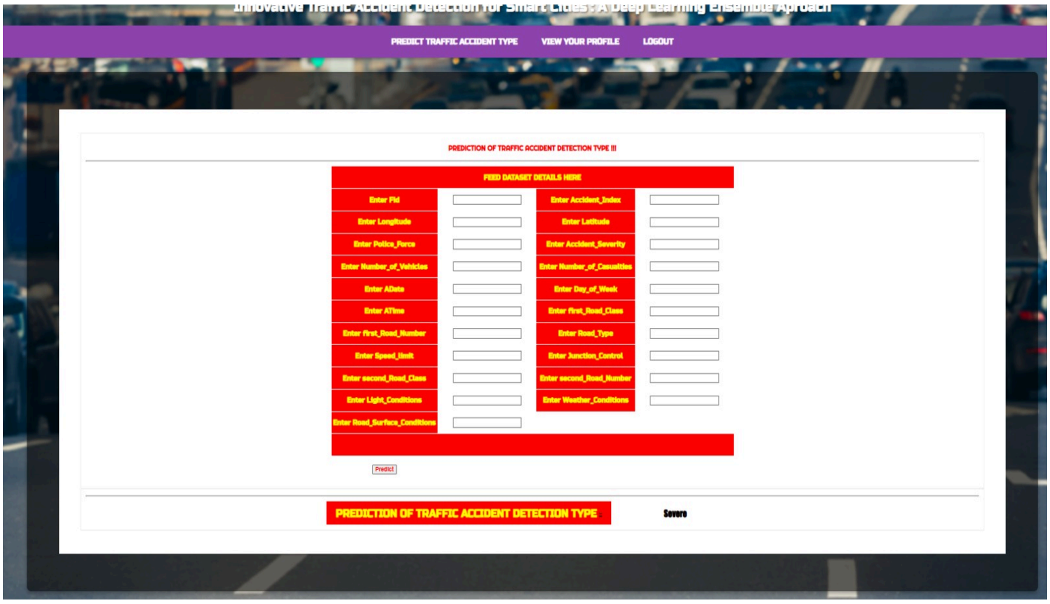

Fig 3: Predicting Data

- True Positives (TP): Correctly detected accidents.
- True Negatives (TN): Correctly identified normal traffic.
- False Positives (FP): Incorrectly flagged normal traffic as accidents.
- False Negatives (FN): Missed accident detections.

Fig 4: User login details

Fig 5: Registration page

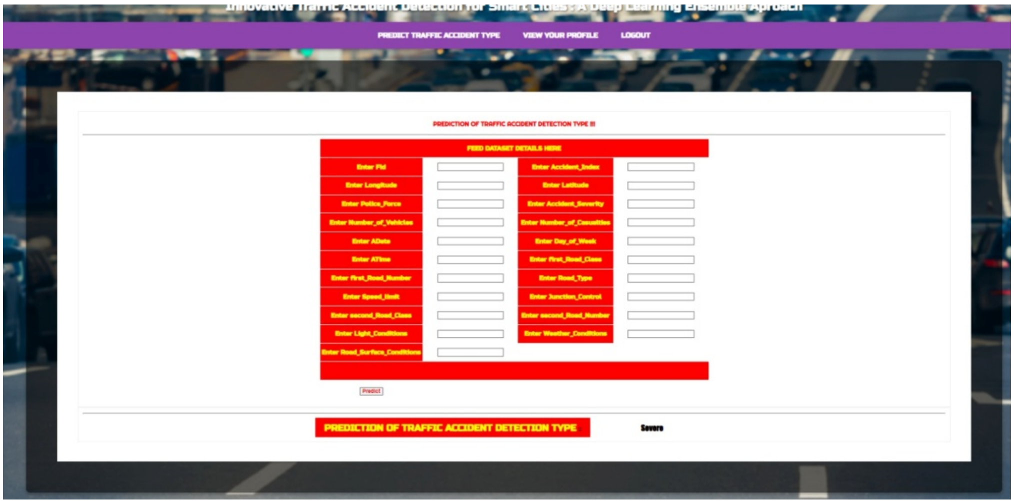

Fig 6: Prediction Data

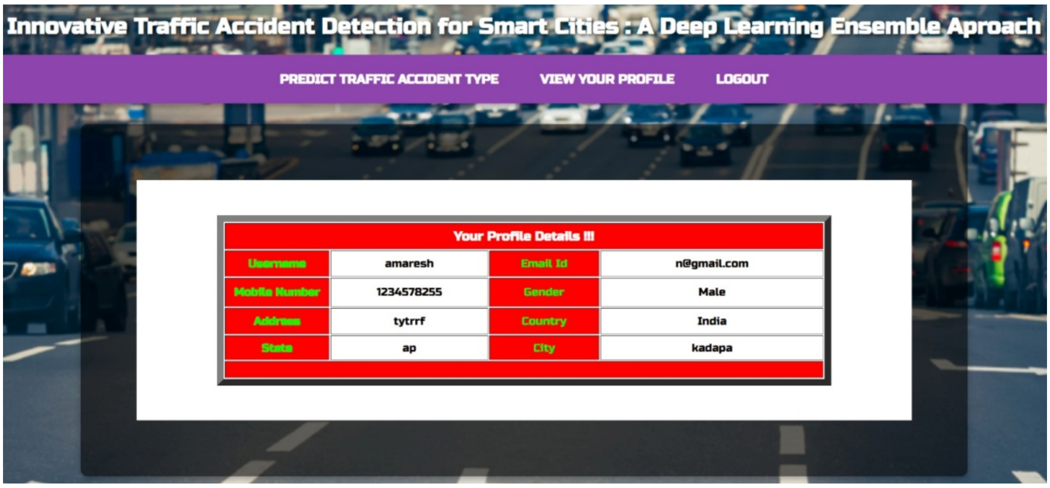

Fig 7: Profile Details

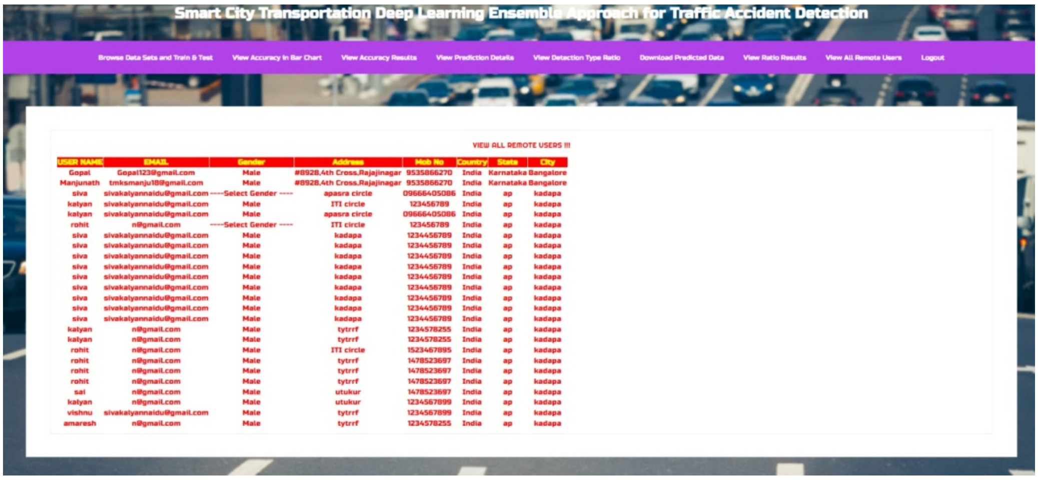

Fig 8: View Users

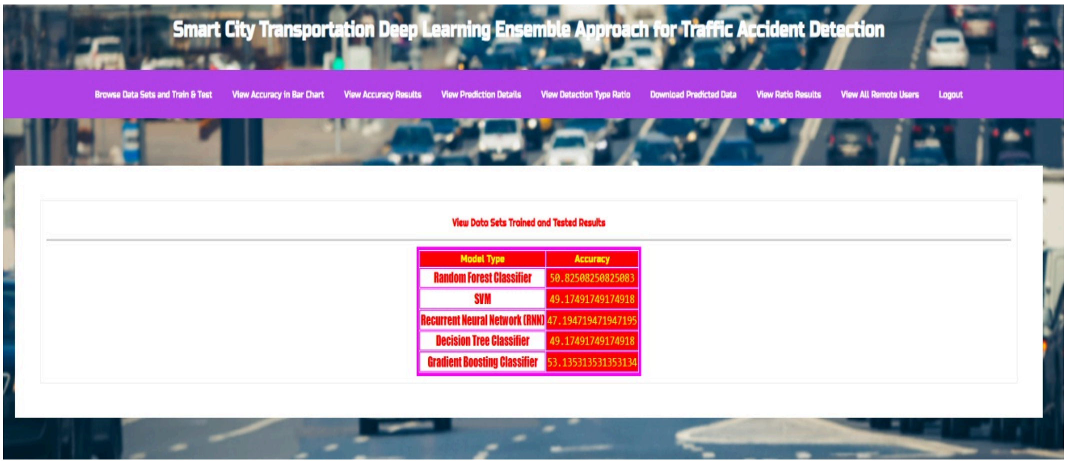

Fig 9: Trained and Tested Data

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Fig 10: View Traffic Details

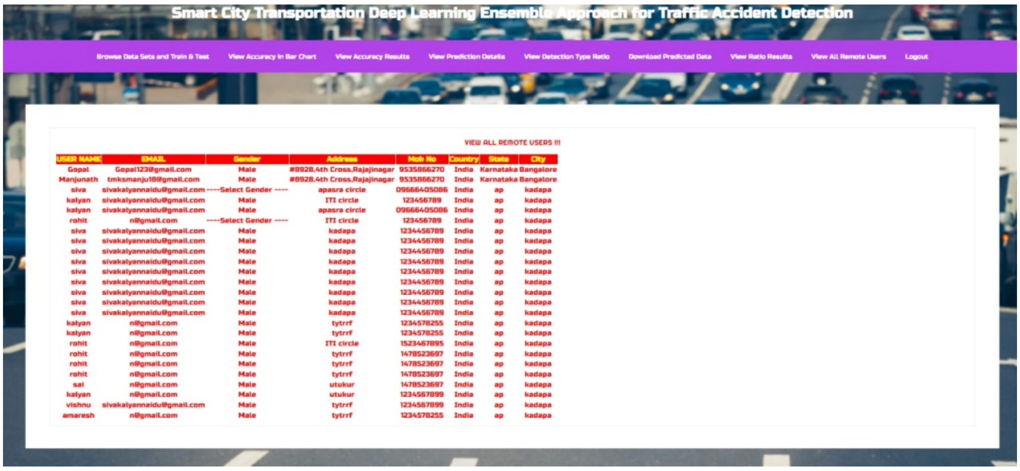

Fig 11: Remote User

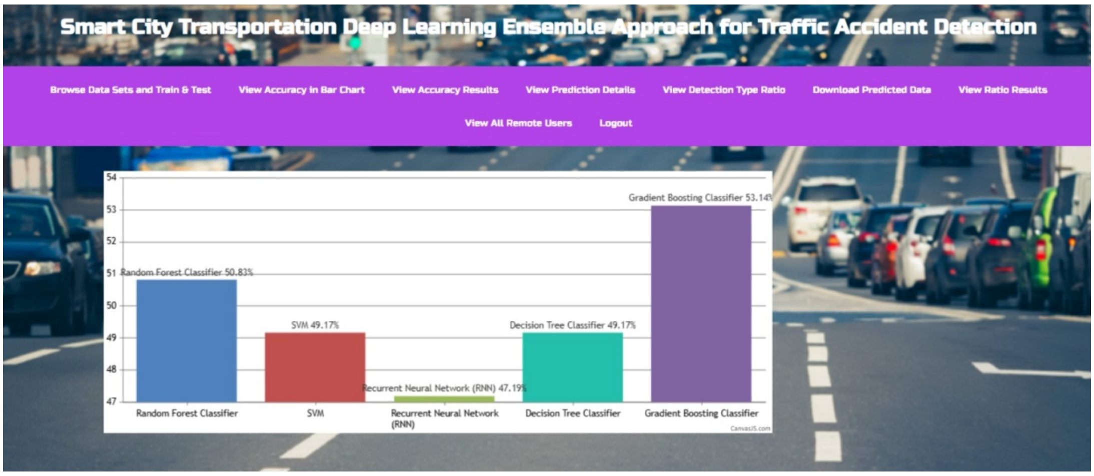

Fig 12: Bar Graph

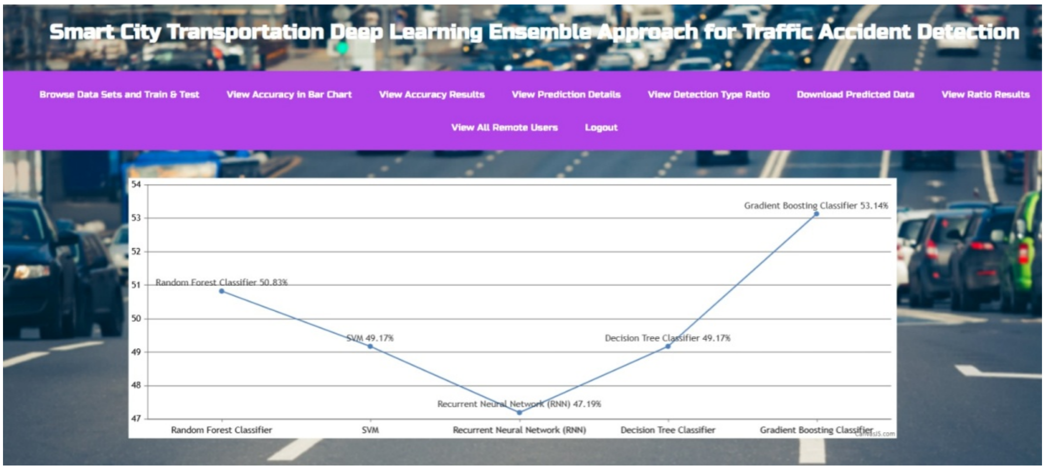

Fig 13: Ratio Results

Fig 14: Line Chart

V. CONCLUSION AND FUTURE WORK

Accurate and efficient traffic accident detection is essential for improving road safety and enhancing smart city transportation systems. This study introduced **the** I3D-CONVLSTM2D model, which integrates RGB frames with optical flow data to effectively identify accidents in real-time. Our approach demonstrated superior performance, achieving an 87% Mean Average Precision (MAP) while addressing challenges such as data imbalance, environmental variations, and computational efficiency. Compared to existing methods, our model balances accuracy and speed, making it suitable for deployment on edge IOT devices for real-time traffic monitoring. Despite its effectiveness, challenges such as occlusions, low-light conditions, and distinguishing between normal congestion and accident scenarios remain. Future work will focus on improving the model's robustness by incorporating multi-modal sensor data and refining algorithms to enhance its adaptability across diverse traffic environments. By advancing accident detection technologies, this research contributes to the development of safer, more efficient urban transportation systems.

Our research also highlights key challenges in accident detection, including data imbalance, environmental variations, occlusions, and computational efficiency. The experimental results demonstrate that integrating optical flow with RGB features enhances accident detection accuracy**,** while transfer learning helps optimize feature extraction. However, distinguishing between traffic anomalies (sudden stops, congestion) and actual accidents remains a challenge, indicating the need for further model improvements.

Future work will focus on multi-modal sensor fusion, incorporating LiDAR, GPS, and radar data to improve robustness in low-visibility conditions and complex urban environments. Additionally, edge AI deployment on lightweight devices like Raspberry Pi and NVIDIA Jetson Nano will enable real-time accident detection without relying on cloud computing. Advanced self-supervised learning and generative AI techniques (GANs**)** will also be explored to enhance dataset diversity and mitigate data imbalance issues. By advancing real-time accident detection models, this research contributes to the development of safer and more intelligent urban transportation infrastructures. The proposed model paves the way for the deployment of smart surveillance systems, AI-driven emergency response mechanisms, and predictive accident prevention strategies, ultimately saving lives and improving road safety worldwide**.**

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