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RESEARCH ARTICLE

PROACTIVE RECOGNITION OF RISKY DRIVING BEHAVIOR OF VEHICLES USING DEEP LEARNING

Nassirou Adamou Hassane[1,2], Boukar Abatchia Nicolas[1] and Mahamadou Issoufou Tiado[1]

1. Faculty of sciences and technology, University of Abdou Moumouni, Niamey, Niger.
2. University Institute of Technology, University of Agadez, Agadez, Niger.

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Abstract

Today, proactive road safety management is essential to reduce the number of accidents, particularly in dense traffic environments. In this context, this study introduces a deep learning framework for predicting vehicle trajectories and identifying risky behaviors from natural traffic data. The developed system combines Yolo and ByteTrack for detection and multi-object tracking and an Lstm seq2seq model to predict future trajectories from short observation windows. From these predictions, three dynamic indicators speed, acceleration, and steering angle are extracted, and a threshold-based mechanism classifies maneuvers as normal or risky. The performance is evaluated using the Ade, Fde, Auc and Eer metrics over different periods of the Ngsim-US101 dataset. The results show moderate prediction accuracy, with higher Ade/Fde errors during periods of dense traffic and a notable improvement when traffic density decreases. The system achieves an AUC of 0.74 and an EER of 0.316, indicating a reasonable ability to distinguish between normal and risky behaviors, while highlighting room for improvement. Analyses also confirm the major influence of traffic density on prediction stability and classification performance.
Overall, this study demonstrates the feasibility and potential of combining detection, tracking, trajectory prediction, and dynamic analysis for proactive recognition of risky behaviors in real-world conditions. These results pave the way for future improvements, particularly by enhancing the thresholding mechanism using adaptive or learning-based strategies.

Introduction:-

In recent decades, road traffic accidents have emerged as a major public health issue posing significant social and economic challenges. According to the World Health Organization (WHO), approximately 1.3 million fatalities occur annually because of road traffic collisions, representing nearly 3% of the Gross Domestic Product (GDP) in most countries(WHO, 2023). A significant proportion of these incidents are attributed to human-related factors, particularly unsafe driving behaviors such as abrupt variations in speed or lane position, and as well as reckless or

Corresponding Author:-Nassirou Adamou Hassane
Address:-Faculty of sciences and technology, University of Abdou Moumouni, Niamey, Niger.
2. University Institute of Technology, University of Agadez, Agadez, Niger.

aggressive maneuvers. The early and automatic recognition of such behaviors constitutes a proactive strategy to reduce accidents and improve traffic flow. In this context, intelligent video surveillance (IVS) emerges as a promising solution. Unlike traditional approaches based on post-accident analysis or human intervention, this approach enables real-time analysis of video scenes by leveraging recent advances in deep learning. These models enable the automatic extraction of relevant features from large-scale data collected from surveillance cameras, in-vehicle sensors, or GPS signals, facilitating the detection and analysis of complex driving behaviors. An intelligent video surveillance system (IVSS) generally relies on three core tasks: object detection; object tracking and behavior recognition. Object detection benefits from the accuracy and efficiency of models such as Faster R-CNN(Girshick, 2015) or YOLO(Redmon et al., 2016). However, object tracking faces various challenges including changes in illumination, partial or complete occlusions, deformations, or high speeds.

Robust algorithms such as DeepSORT (Wojke et al., 2017), FairMOT (Zhang et al., 2021), or ByteTrack (Zhang et al., 2022) are commonly employed to address these challenges. Finally, behavior recognition, the high-level task of an IVS, builds upon the outputs of the preceding steps to analyze interactions between objects. The primary models used to accomplish this task are Recurrent Neural Networks such as Long Short-Term Memory (LSTM) and Graph Neural Networks (GNN) (Corso et al., 2024; Yu et al., 2019).This hierarchical approach enables the system to effectively monitor complex traffic scenarios and detect risky driving behaviors.Building on these advances, the present work proposes a proactive model based on deep learning techniques for the recognition of risky driving behaviors in road traffic. After reviewing existing approaches, we present the adopted methodology and the experimental results obtained and conclude with the perspectives offered by this research.

Literature Review:-

In recent years, the rise of artificial intelligence and deep learning has significantly advanced the application of IVS to road safety. In this context, several researchers have explored the problem of recognizing abnormal driving behaviors through various approaches to reduce the occurrence of road accidents.In(Yang and Zhao, 2022), authors proposed a model for risky driving recognition specifically applied to smoking and mobile phone use while driving. Their approach is based on the use of the YOLOv5 network combined with the Coordinated Attention (CA) mechanism to improve detection accuracy. In addition, the authors introduced the computation of the Euclidean distance and elbow angle analysis to refine the initial predictions. The proposed model achieved a mean accuracy of 93.4% with an inference speed of approximately 61 FPS, demonstrating its effectiveness. However, this model focuses on specific behaviors and may not generalize well to other risky actions such as aggressive steering or abrupt lane changes.

Similarly, (Abosaq et al., 2022)proposeda Convolutional Neural Network (CNN) for the recognition of abnormal driver behaviors using a dedicated dataset comprising five behavioral classes. A comparative performance study of this model with other pre-trained models namely ResNet101, VGG-16, VGG-19 and Inception-v3 was carried out by the authors. An accuracy of 95%, higher than that of the pre-trained models, demonstrates its ability to effectively classify abnormal behaviors.A TrafficSensor**,** anIVS composed of two modules: the first performs vehicle detection and classification, whereas the second is responsible for tracking, was presented in (Fernández et al., 2021). After comparing several models, YOLOv3 and YOLOv4 trained on a dedicated dataset were selected for the detection module. The tracking module combines a simple spatial association algorithm with a Kanade–Lucas–Tomasi (KLT)tracker to enhance robustness and accuracy. This modular approach demonstrates the advantage of integrating complementary techniques for reliable vehicle monitoring.

Other research has employed trajectory analysis to recognize traffic behaviors.In (Zhang and Sung, 2023),authors proposed an accident detection method based on trajectory tracking and spatio-temporal analysis using influence maps. Using the YOLOv5 model and the DeepSORT algorithm, they first extracted vehicle trajectories and then employed a CNN to identify accidents from the generated maps. The method achieved a detection accuracy of 95%, underscoring its effectiveness in accident recognition.Banifakhr and Sadeghi (Banifakhr and Sadeghi, 2021)proposed a combination of heterogeneous classifiers, including optimized CNNs, fuzzy neural networks (ANFIS), and autoencoders, to detect traffic anomalies. Their model employs decision fusion, where the CNN-ANFIS combination classifies each trajectory and the autoencoders verify whether it is normal or abnormal. This approach achieved strong performance in recognizing abnormal trajectories, highlighting the relevance of the multi-model strategy for robust anomaly detection.

Santhosh et al. (Santhosh et al., 2021) proposed a hybrid approach for classifying vehicle trajectories in traffic, combining Convolutional Neural Networks (CNNs) and Variational Autoencoders (VAEs). The approach achieved an accuracy improvement of 1–6% compared to several conventional neural classifiers, highlighting the effectiveness of hybrid architectures for trajectory classification tasks.Karishma and Vahida(Pawar and Attar, 2022) proposed a deep learning-based approach for the automatic detection and localization of road accidents by framing the task as an anomaly detection problem. The method adopts a one-class classification strategy, employing a spatio-temporal autoencoder and a sequence-to-sequence Long Short-Term Memory (LSTM) autoencoder to model spatial and temporal representations in the video. The proposed model was evaluated onreal-world video traffic surveillance datasets and significant results have been achieved both qualitatively and quantitatively.

In (Mao et al., 2024),authors propose Traffic-ConvLSTM to detect urban traffic anomalies. The model combines CNNs and LSTMs to convert traffic trajectories into image representations to capture spatial relationships among roads, traffic flow, and surroundings. It uses convolution kernels of varying sizes to extract features at road, regional, and city levels, while also modeling temporal patterns across hourly, daily, and weekly scales. By assigning adaptive weights to different spatial and temporal features, Traffic-ConvLSTM captures complex correlations in traffic anomalies. The approach outperforms existing methods in detecting long-term, city-scale anomalies and identifies notable irregularities during holidays and major events, offering insights into urban traffic control and management. These studies demonstrate a variety of approaches for detecting road traffic incidents. Although the reported results are promising, implementing proactive measures is necessary to reduce the occurrence of accidents.

Materials and Methods:-

Overview:-

In this study, we present a hybrid framework designed to recognizeproactively risky driving behaviors in road traffic. We focus on three types of behaviors: speed instability, characterized by repeated acceleration and deceleration phases; unstable steering, indicated by lateral oscillations across the lane; and aggressive maneuvering, reflected by abrupt accelerations and braking. These behaviors increase accident risk and disrupt traffic flow (Chen et al., 2021; Quddus, 2013; Zhang et al., 2013).

Our proposed pipeline, presented in Figure 1, combines:

1. Vehicle detection and tracking using a convolutional neural network (CNN);
2. Trajectory prediction using a recurrent neural (RNN) with a sequence-to-sequence architecture;
3. Risk recognition based on feature-derived thresholding rules.

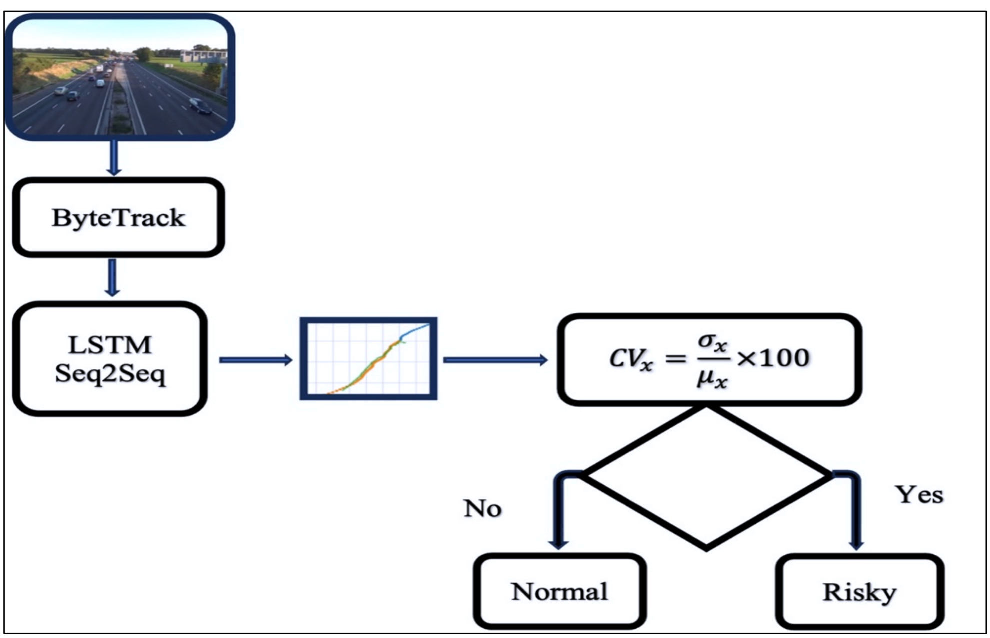

Figure 1: The proposed methodology pipeline

Vehicle Detection and Tracking:-

Vehicle detection is performed frame-by-frame using YOLO11(Jocher et al., 2023), restricted to the classes$V = \{\text{bus}, \text{car}, \text{motorcycle}, \text{truck}\}$. Only detections with confidence scores above a minimum treshold r_{min} are retained. Vehicle tracking is then carried out using the ByteTrack algorithm (Zhang et al., 2022),which links detections across frames to reconstruct trajectories. For each tracked vehicle, the trajectory is represented as:

$$\mathbf{T} = \{(\mathbf{x_1}, \mathbf{y_1}), (\mathbf{x_2}, \mathbf{y_2}), \dots, (\mathbf{x_n}, \mathbf{y_n})\} \tag{1}$$

where(x_i, y_i) denotes the tvehicle position in frame i.

Trajectory Prediction:-

For trajectory forecasting, we define an observation window of length T_{OBS} :

$$\mathbf{T}_{\text{OBS}} = \{(\mathbf{x_1}, \mathbf{y_1}), (\mathbf{x_2}, \mathbf{y_2}), \dots, (\mathbf{x}_{\mathbf{T}_{\text{OBS}}}, \mathbf{y}_{\mathbf{T}_{\text{OBS}}})\} \tag{2}$$

The goal is to predict the future positions over prediction horizon T_{PRED}:

$$\mathbf{T}_{\text{PRED}} = \{(\mathbf{x}_{\mathbf{T}_{\text{OBS}}+\mathbf{1}}, \mathbf{y}_{\mathbf{T}_{\text{OBS}}+\mathbf{1}}), (\mathbf{x}_{\mathbf{T}_{\text{OBS}}+\mathbf{2}}, \mathbf{y}_{\mathbf{T}_{\text{OBS}}+\mathbf{2}}) \dots, (\mathbf{x}_{\mathbf{T}_{\text{OBS}}+\mathbf{T}_{\text{PRED}}}, \mathbf{y}_{\mathbf{T}_{\text{OBS}}+\mathbf{T}_{\text{PRED}}})\} \tag{3}$$

We employ sequence-to-sequence (Seq2Seq) architecture with Long Short-Term Memory (LSTM) units for both encoder and decoder **Figure 2.** The encoder processes T_{OBS} and compresses it into a context vector that summarizes past motion dynamics, which is then used by the decoder to generate the T_{PRED}.

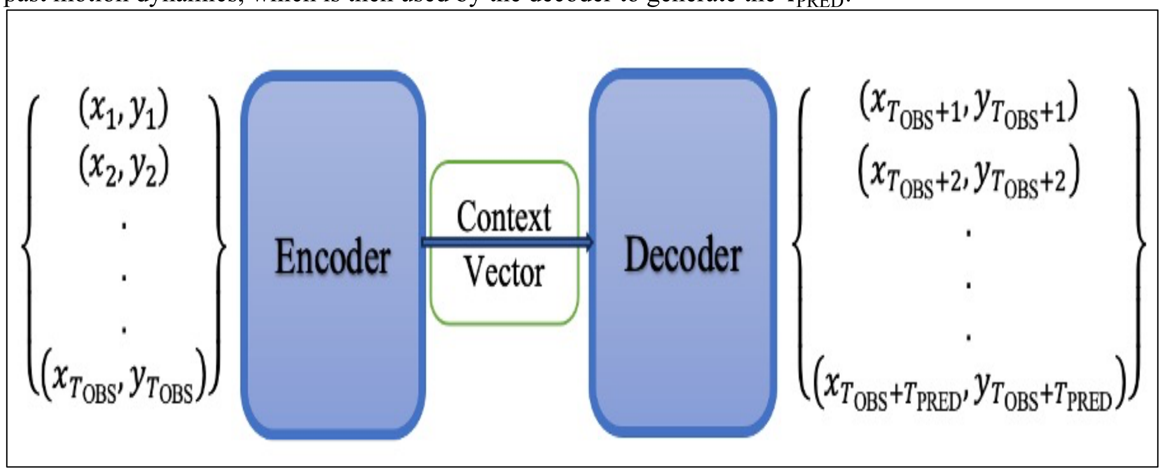

Figure 2: The LSTM Seq2Seq architecture

The model parameters are optimized by minimizing the Mean Squared Error (MSE) between the predicted and the ground-truth positions:

$$\mathbf{MSE} = \frac{\mathbf{1}}{|\mathbf{T}_{\text{PRED}}|} \sum_{\mathbf{t}=\mathbf{1}}^{|\mathbf{T}_{\text{PRED}}|} \left\| \hat{\mathbf{y}}_{\mathbf{T}_{\text{OBS}}+\mathbf{t}} - \mathbf{y}_{\mathbf{T}_{\text{OBS}}+\mathbf{t}} \right\|^{\mathbf{2}} \tag{4}$$

where $|T_{PRED}|$ denotes the length of T_{PRED}

Risk Recognition via Thresholding

The evaluated trajectory is defined as the concatenation of observed and predicted positions:

$$\mathbf{T_{EVAL}} = \mathbf{T_{OBS}} \cup \mathbf{T_{PRED}} \tag{5}$$

For each motion indicator speed(v), steering angle (θ), and acceleration(a), which are determined from vehicle's positions, we compute the coefficient of variation (CV)(Canchola et al., 2017). This coefficient is a unitless metric that quantifies how each quantity varies relative to its mean:

$$\mathbf{CV_x} = \frac{\boldsymbol{\sigma}_\mathbf{x}}{\boldsymbol{\mu}_\mathbf{x}} \times \mathbf{100} \tag{6}$$

where σ_x et μ_x are the standard deviation and mean of indicator $x \in \{v, \theta, a\}$. Risk is identified when at least one CV_x exceeds its predefined threshold. Consequently, the task of risky driving recognition is formulated as a binary classification problem, where normal driving is labeled as 0 and risky driving as 1.

Dataset and Preprocessing:-

We use the Next Generation Simulation (NGSIM) US-101 dataset(U.S. Department of Transportation, n.d.), containing vehicle trajectories recorded at 10 Hz. Each trajectory contains detailed information such as position, speed, and acceleration; however, only the variables listed in **Table 1** are retained in this study.These data have been widely exploited in trajectory prediction and driving behavior analysis research like (Altché and de La Fortelle, 2017; Deo and Trivedi, 2018).

Table 1. Considered variables from NGSIM US-101

Name	Description	Unit
Vehicle_ID	Vehicle identifier	—
Frame_ID	Frame identifier	—
Local_X	Lateral position	feet
Local_Y	Longitudinal position	feet

The preprocessing pipeline involves several steps. First, the spatial coordinates were converted from feet to meters using the conversion factor 1 ft = 0.3048 m. To reduce noise while preserving motion patterns, a Savitzky-Golay filter(Savitzky and Golay, 1964) is applied to smooth trajectories. Finally, the processed trajectories are segmented using an 8-second sliding window consisting of 3-second observation phase and 5-second prediction horizon, to generate the input-output sequences for model training.

Result and Discussions:-

In this section, we present the results obtained throughout this study. We first evaluated the performance of the proposed LSTM encoder-decoder model for vehicle trajectory prediction. This model is then integrated into the overall framework designed to recognize the risky driving behaviors in traffic. Finally, we discuss the performance of the global model and its ability to accurately identify different types of risky maneuvers.

Trajectory Prediction Performance:-

The NGSIM dataset, described in the previous section, was collected over a 45-minute period divided into three 15-minute segments: from 7:50–8:05, 8:05–8:20, and 8:20–8:35. The LSTM encoder–decoder network was evaluated on data from each period using a 70/15/15 split for training, validation, and testing, respectively. The model was trained for 100 epochs with the Adam optimizer and MSE loss function and evaluated using the Average

Displacement Error (ADE) and Final Displacement Error (FDE) metrics defined as:

$$\mathbf{ADE} = \frac{\mathbf{1}}{|\mathbf{T}_{\mathrm{PRED}}|}\sum_{\mathbf{t=1}}^{|\mathbf{T}_{\mathrm{PRED}}|}\left\|\hat{\mathbf{y}}_{\mathbf{T}_{\mathrm{OBS}}+\mathbf{t}} - \mathbf{y}_{\mathbf{T}_{\mathrm{OBS}}+\mathbf{t}}\right\| \quad (7)$$

$$\mathbf{FDE} = \left\|\hat{\mathbf{y}}_{\mathbf{T}_{\mathrm{OBS}}+\mathbf{T}_{\mathrm{PRED}}} - \mathbf{y}_{\mathbf{T}_{\mathrm{OBS}}+\mathbf{T}_{\mathrm{PRED}}}\right\| \quad (8)$$

Table 2: The ADE and FDE for different period of NGSIM US-101

Period	ADE (m)	FDE(m)
7:50 to 8:05	1.953	4.760
8:05 to 8:20	1.877	4.739
8:20 to 8:35	1.856	4.670

Table 2 summarizes the proposed model performance across time segments. Both ADE and FDE decrease slightly over time, indicating stable and robust predictive performance. This consistency suggests that the LSTM encoder-decoder effectively captures temporal dependencies in vehicle motion, maintaining generalization even under denser traffic conditions.These findings align with prior research (Deo and Trivedi, 2018; Messaoud et al., 2021; Neumeier et al., 2023) which demonstrated the ability of recurrent sequence-to-sequence architecture to model long-term motion patterns in heterogeneous and dynamic traffic environments.

Evaluation of the proposed framework:-

The performance of the proposed risky driving recognition framework is evaluated using the Area Under the Receiver Operating Characteristics Curve (AUC) and the Equal Error Rate (EER), two metrics that enable a threshold-independent assessment of the classifier. The AUC, computed from the ROC curve plotting True Positive Rate (TPR) against False Positive Rate (FPR), measures the overall separability between normal and risky driving behaviors. An AUC = 1 indicates the perfect discrimination, whereas AUC = 0.5 indicates correspond to the random classification.

The EER is defined as the point where the False Acceptance Rate (FAR) equals the False Rejection Rate (FRR). A low EER reflects a better ability to distinguish normal from risky driving. This point also corresponds to the position on the ROC curve where FPR = 1 – TPR.**Table 3** highlights how the model's performance evolves across three consecutive time intervals, revealing a clear improvement after the first period. During the initial interval, the model achieved an AUC of **0.74**, indicating only a moderate capacity to discriminate between normal and risky driving behaviors. The corresponding EER of **0.316** further confirms the limited class separability at this stage, suggesting that the decision threshold still results in a relatively high rate of misclassification.

In contrast, across the last two intervals, the model demonstrates increased stability and stronger discriminative performance. The higher AUC of **0.85**, combined with the reduced EER of **0.211**, reflects a more robust and consistent ability to distinguish risky from normal driving. These findings also align with the observations reported in **Table 2**, where the first period is associated with higher ADE and FDE values. This initial degradation in performance is likely linked to the higher traffic density during the first interval, which makes driving behaviors more complex and more difficult to predict. Conversely, the gradual decrease in traffic density during the final two periods likely contributes to more stable vehicle trajectories, ultimately leading to improved model performance in these later intervals.

Table 3: AUC and EER across different time periods

Period	AUC (%)	EER(%)
7:50 to 8:05	74	31.6
8:05 to 8:20	85	21.1
8:20 to 8:35	85	21.1

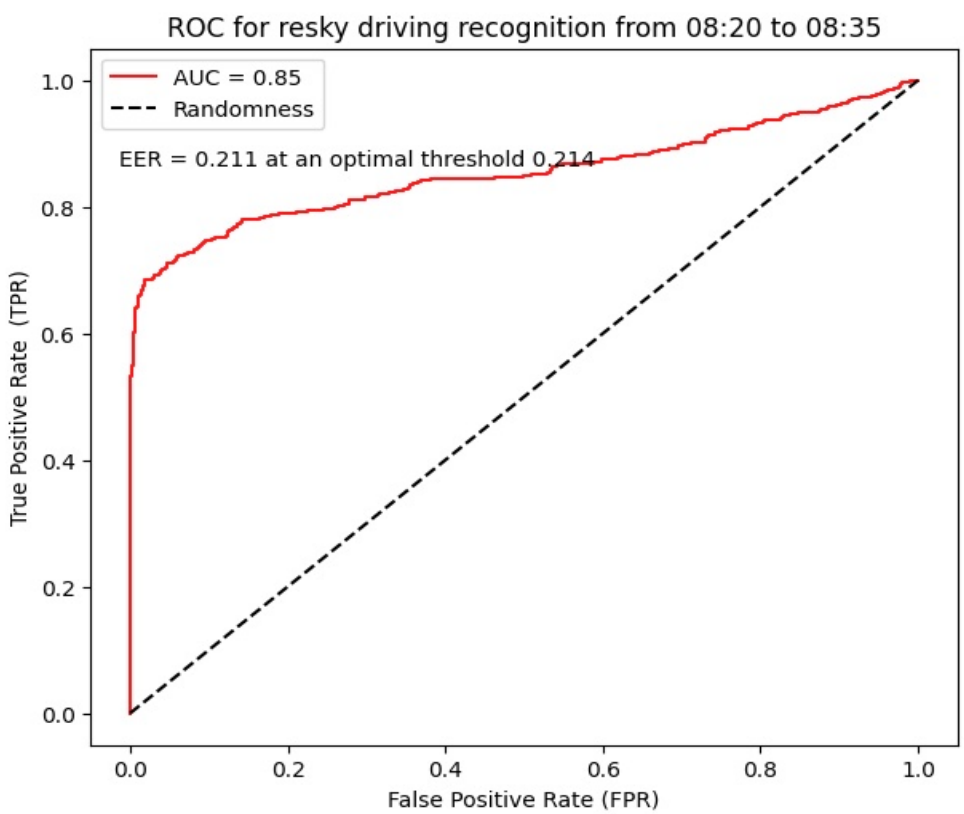

Figure 3: The ROC curve obtained from 08:20 to 08:35

Conclusion:-

In this article, we present a deep learning–based framework for recognizing risky behaviors in road traffic. By combining YOLO-ByteTrack for vehicle detection and tracking with an LSTM seq2seq trajectory-prediction model, we built a system capable of learning motion patterns from short observation windows. By predicting future trajectories and extracting dynamic indicators—namely speed, acceleration, and steering angle—we applied a threshold-based decision mechanism to classify vehicle maneuvers as normal or risky. The experimental results demonstrate that the proposed framework offers a promising solution for proactive detection of risky behaviors in complex traffic environments. Performance analysis across the different time intervals revealed a moderate discriminative ability under high-density traffic conditions.

However, notable improvements were observed as traffic flow decreased, leading to more stable and reliable trajectory predictions. This highlights both the strengths and limitations of trajectory-based risk assessment and shows the sensitivity of prediction accuracy to variations in traffic density. Overall, this study confirms the potential of deep sequential models for proactive road safety analysis. Future work may explore the integration of multimodal information (e.g., visual context, driver behavioral cues, road topology), improvements to the thresholding mechanism through adaptive or learning-based strategies, and real-time implementation. Such extensions are expected to enhance the robustness, scalability, and generalization capabilities of risky-driving recognition systems in real-world conditions.

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