

Research Article

Federated Deep Learning for Tailgating Behaviour Detection in Intelligent Transportation Systems

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Article Info	Abstract
Article History	Tailgating, which occurs when a vehicle follows another at an unsafe distance, is a major contributor to rear-end collisions, especially on roads with dense traffic, frequent lane changes, and limited infrastructure, creating hazardous conditions. Modern intelligent transportation systems and connected vehicle technologies help monitor and reduce unsafe behaviours. Still, conventional deep learning methods rely on centralised training, which raises concerns about privacy, scalability, and delays. This framework integrates collaborative training with federated learning and a bidirectional long short-term memory network to detect tailgating accurately. Realistic vehicle trajectory data were generated using the Simulation of Urban mobility tool to replicate diverse driving scenarios, including urban and highway conditions. Key features such as following distance, relative speed, braking distance, time headway, vehicle speed, and driver reaction distance were derived to model driving behaviour. Baseline models, including convolutional neural networks, recurrent neural networks, and long short-term memory networks, were developed for comparison. The results show that the framework combining federated learning and a bidirectional long short-term memory network achieved detection accuracy above 91.98%, outperforming centralised training and baseline models. The study shows that a collaborative, decentralised approach can capture bidirectional temporal dependencies in driving sequences, ensuring driving data remains local while supporting real-time detection.
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1. Introduction

In 2022, the Ministry of Road Transport and Highways reported that there were 461,312 road accidents in India, resulting in 168,491 deaths and 443,366 injuries [1]. India has one of the highest numbers of fatalities caused by road accidents globally. Among these accidents, 32.9% occurred on national highways and expressways, 23.1% on State Highways, and 43.9% on other roads. Approximately 68% of road accident deaths occurred in rural areas, while 32% occurred in urban areas. Excessive speeding remains the leading cause of such incidents. Intelligent transportation systems (ITS) have emerged as an

essential component of modern traffic management and road safety solutions[2]. Intelligent communication and data analytics play a key role in enhancing road network safety by enabling real-time monitoring and decision-making. ITS technologies can be integrated into connected and autonomous vehicles, which rely on onboard sensors and cameras along with road infrastructure to enable seamless vehicle-to-vehicle, vehicle-to-infrastructure, and vehicle-to-everything communications. This integration facilitates safer and more efficient traffic flow, helping to mitigate aggressive driving behaviours such as tailgating. Tailgating is an aggressive driving behaviour in which one vehicle follows another too closely, leaving insufficient distance to stop safely if the leading vehicle brakes suddenly. An example of a rear-end collision caused by tailgating is illustrated in Figure 1. Detecting tailgating is challenging due to changing traffic conditions, unpredictable human behaviour such as distraction and reaction time, varied vehicle dynamics, and growing concerns about data privacy and security.

Recent advances in artificial intelligence, machine learning (ML), and deep learning (DL), supported by cloud, edge, or fog computing and modern network infrastructure, have significantly improved the performance of tailgating detection systems. Conventional training of ML and DL models typically relies on centralised data collection, whereby data from various sources is aggregated on a central server. However, this centralised approach raises concerns related to privacy, requires substantial computational resources, offers limited scalability, and increases communication latency. Federated learning (FL) is a decentralised approach that addresses these challenges by enabling collaborative model training without sharing raw data [3, 4]. In FL, the global model is typically processed centrally on a server, while local models are trained independently on distributed edge devices using local data. Instead of transmitting raw data, only model updates are communicated to the central server, which aggregates these updates to improve the global model. This framework preserves privacy and reduces the need for large-scale data transmission.

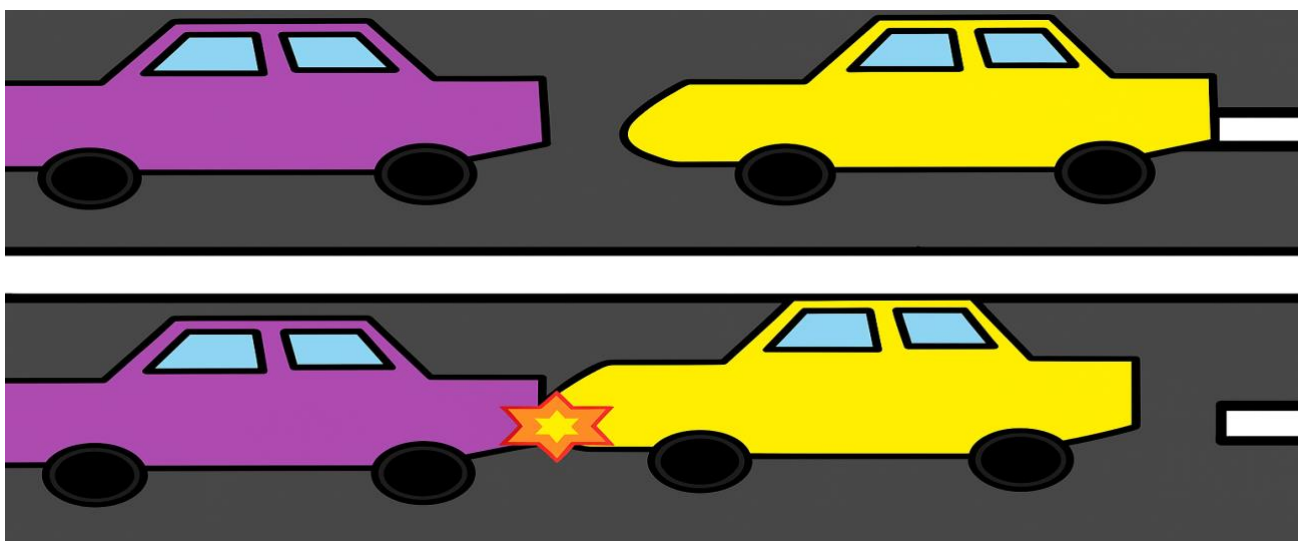


Figure 1. Rear-end collision caused by tailgating

In this study, FL is used to process time-dependent sequences and capture the dynamics of vehicle movements for tailgating detection. Edge devices in the FL framework are represented by road vehicles simulated using the Simulation of Urban MObility (SUMO) platform. A realistic and comprehensive local dataset is generated for various driving scenarios. Parameters computed from the dataset, such as following distance, relative speed, and braking distance, along with derived features like driver reaction time and safety margin, are used as inputs for bidirectional long short-term memory (Bi-LSTM), long short-term memory (LSTM), convolutional neural networks (CNN), and recurrent neural networks (RNN) models within the FL framework.

The main contributions of this paper are as follows:

- 1) Design of a federated learning-based framework for tailgating detection.
- 2) Generation of realistic and comprehensive local datasets for DL models using SUMO.
- 3) Implementation of data pre-processing and feature engineering to compute primary and derived parameters relevant to tailgating.
- 4) Development of conventional DL models such as LSTM, CNN, and RNN for tailgating detection.
- 5) Development and evaluation of FL-based versions of these models, including Bi-LSTM.
- 6) Performance comparison of DL models trained with and without FL for tailgating detection.

2. Literature Review

Rear-end collisions and tailgating behaviour continue to be significant issues in road safety research. Early studies, such as [5], examined naturalistic driving data to identify tailgating as an emerging habit, emphasising the challenge of recognising these behaviours amid dynamic traffic conditions. Building on this, Shahverdy, et al. [6] demonstrated that classifying driver behaviour can be enhanced with DL, transforming vehicle signals into images analysed by CNNs, which improves accuracy while maintaining privacy.

Beyond CNNs, fuzzy logic has been employed to address stress and impatience in driving [7], although its scalability in real-time systems is limited due to the growing complexity of rules. To model human emotions, Khadim, et al. [8] introduced a cognitive agent approach, demonstrating how fear-based modelling can enhance safety for non-connected vehicles.

Precise positioning is also crucial: Williams and Barth [9] integrates onboard sensors and radio frequency identification (RFID) to achieve lane-level precision, addressing the limitations of the global navigational satellite system (GNSS). Additionally, Knowles Flanagan, et al. [10] investigated how the reliability of vehicle-to-vehicle (V2V) communication influences braking distances, highlighting the significance of robust data transmission for ensuring safe vehicle interactions. Similar vehicle-to-everything (V2X) frameworks, such as Xia and Chen [11], demonstrate how federated learning, combined with multi-radio V2X technologies, can enhance collaborative driving decisions for collision avoidance.

Several works focus on innovative detection methods. For example, Luo, et al. [12] presented an ETC big-data approach for detecting threat vehicles at low speeds on expressways, while [13] and [14] emphasised collision prediction in vehicular ad-hoc networks (VANETs) using machine learning models, showing a reduction of up to 77% in accidents when predictive warnings are issued on time. Reinforcement learning and cooperative systems further enhance this: Naji, et al. [15] integrated deep reinforcement models with brake reaction time analysis to assess rear-end risk, demonstrating that human factors, such as driver distraction, significantly impact the likelihood of collisions.

Trajectory prediction has gained importance, especially for intersections and lane-change scenarios., Sheikh and Peng [16] comprehensively reviewed trajectory planning algorithms and user expectations, and [17] advanced this by developing sequence-to-sequence RNNs for conflict identification using bounding boxes for better geometric accuracy. Similarly, Djenouri, et al. [18] demonstrated a forward collision warning system for motorcyclists that predicts time-to-collision using LSTM models and smartphone sensors.

To improve prediction accuracy, DL models such as LSTM and Bi-LSTM have shown strong performance. Yuan, et al. [19] demonstrated that LSTM and RNNs can effectively predict real-time crash risk by learning temporal driving patterns, reinforcing the relevance of sequential models for safety analysis. Similarly, [20] and [21] reported that Bi-LSTM networks and self-attention layers can classify near-crash events and predict driving risks using multi-source data, outperforming traditional models. In the same vein, [22] and [23] presented novel LSTM frameworks and ensemble multi-layer perceptrons optimised for rear-end collision prediction in Internet of vehicles contexts.

FL emerges as a promising solution to address privacy and decentralisation challenges in ITS. Studies such as [24] and [25] explored FL's potential in vehicular networks, demonstrating how collaborative training enhances safety without requiring the exchange of raw data. Likewise, Tang, et al. [26] introduced communication-efficient FL for autonomous braking, and Yuan, et al. [19] showed how digital twins can enhance FL for real-time collision warnings.

However, while these methods address collision risk modelling [27, 28], driver behaviour classification [29], and autonomous braking systems [30], they often rely on centralised architectures. Importantly, none of them combine FL with Bi-LSTM architectures to specifically target tailgating behaviour detection under decentralised, realistic urban mobility scenarios, such as those modelled by SUMO simulations.

Despite significant advances in collision prediction, trajectory planning, and federated frameworks for connected vehicles, a critical gap remains in the development of privacy-preserving tailgating detection. Existing studies either use single-point detection models or centralised DL, which struggle with dynamic, time-dependent vehicle interactions and privacy constraints. Therefore, this work addresses this gap by

designing a robust FL-Bi-LSTM framework that captures bidirectional temporal dependencies in driving sequences, leveraging realistic SUMO-generated data while preserving data privacy and ensuring scalability across distributed edge clients.

3. Methodology

This study develops a novel FL framework that integrates a Bi-LSTM DL model to detect tailgating behaviour in vehicular networks. The core idea is to enable multiple vehicles to collaboratively train a shared predictive model while ensuring that raw driving data remains decentralised at the edge, thereby addressing the privacy, scalability, and latency challenges commonly encountered in centralised architectures.

The architecture operates in three stages. First, realistic driving scenarios are simulated using the SUMO platform to generate spatiotemporal vehicular behaviour data under diverse traffic conditions, including varying road types, vehicle densities, and driver behaviours. This data forms the basis for training each client's local model. Second, local models are trained independently on each vehicle's dataset using a Bi-LSTM network, which is well-suited for time-series analysis due to its ability to capture both past and future temporal dependencies. Third, only the model updates, rather than raw data, are communicated to a central server, where they are aggregated using federated averaging (FedAvg) to refine a global model. This process repeats iteratively until the global model converges.

The overall workflow is illustrated in Figure 2, which depicts the flow of data from local collection and preprocessing to local model training, parameter aggregation, and global model update. This design ensures that sensitive driving behaviour data never leaves the vehicle, enhancing compliance with data privacy standards while improving model generalisation through diverse distributed data sources.

3.1 Data Collection

A customised dataset was developed using the SUMO open-source microscopic traffic simulator to replicate realistic driving conditions across urban and highway road segments in Bangalore. The study area was extracted from OpenStreetMap (OSM) data and converted into SUMO-compatible format, ensuring the inclusion of multiple intersections, lane merges, and road segments that realistically reflect both dense urban traffic and highway corridors. Random vehicle trips were generated using SUMO's `randomTrips.py` tool to simulate varied vehicle interactions and moderate to heavy traffic flows over a continuous simulation period of one hour. Each simulation run recorded detailed vehicle trajectory information at every timestep using SUMO's floating car data output. The raw dataset captured core spatiotemporal information for every vehicle, including simulation time, vehicle ID, position coordinates, lane ID, instantaneous speed, acceleration or deceleration, leader-follower relationships, road types classified as urban or highway, and traffic density for each segment. This raw trajectory data provided a comprehensive snapshot of how

vehicles interact with their surroundings in different road contexts and traffic conditions. Approximately 100,000 raw data points were collected, spanning multiple traffic scenarios to ensure behavioural diversity. To replicate a realistic FL scenario, the data was distributed across various vehicles acting as independent local clients, with no raw data shared between them. Each local dataset was divided into 70 percent for training and 30 percent for testing and validation, preserving a non-independent and identically distributed data (non-IID) distribution that mirrors real-world driving behaviour where vehicles experience unique trips and conditions.

3.2. Data Pre-processing and Feature Engineering

To ensure that the tailgating detection framework performs accurately under varying traffic conditions, the raw data generated through SUMO simulation is subjected to a robust pre-processing and feature engineering pipeline. This process begins with cleaning the dataset to handle missing values, removing outliers, and verifying the consistency of the parameters collected across different simulated driving scenarios. The primary parameters essential for modelling driver behaviour include the following distance, relative speed, braking distance, time headway, road type, traffic density, vehicle speed, and vehicle acceleration or deceleration. Each parameter is derived to capture the spatiotemporal dynamics critical for tailgating detection.

The following distance, denoted as $D_f(t)$ measures the gap between a following vehicle and the vehicle directly ahead at time t . This metric is fundamental for evaluating whether a safe distance is maintained. Complementing this, the relative speed between the two vehicles is calculated to assess whether the following vehicle is approaching or distancing itself from the leader. This relative speed, $V_r(t)$ is defined by (1):

$$V_r(t) = V_{following}(t) - V_{leading}(t) \quad (1)$$

where $V_{following}(t)$ is the speed of the following vehicle at time t , and $V_{leading}(t)$ is the speed of the leading vehicle at the same time. This relationship serves as a dynamic indicator of potential tailgating risk when combined with other variables. Another vital parameter is the braking distance, $D_b(t)$, which represents the minimum distance required for a vehicle to come to a complete stop, assuming maximum deceleration. This is computed using the well-established kinematic relationship (2),

$$D_b(t) = \frac{[V_{following}(t)]^2}{(2a_{max})} \quad (2)$$

where a_{max} is the maximum deceleration capacity of vehicle. Comparing $D_b(t)$ with the actual following distance $D_f(t)$ helps determine if a vehicle has sufficient space to stop safely under emergency conditions.

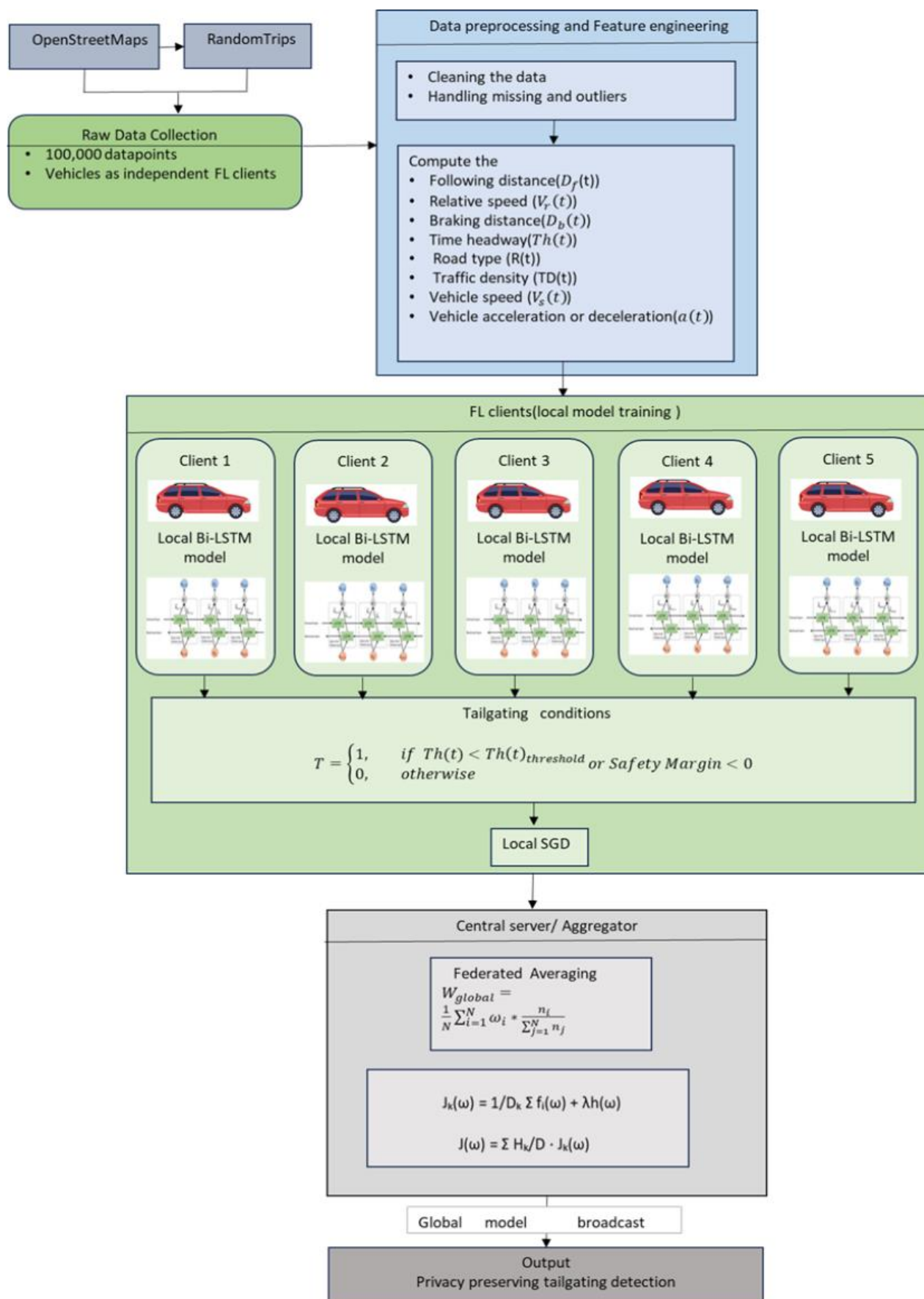


Figure 2. Federated learning-based framework for tailgating detection using locally trained Bi-LSTM models and global aggregation.

In addition to distance and speed, the time headway, $Th(t)$, provides an essential temporal measure, indicating the time gap available for a driver to respond to any sudden changes in the leading vehicle's motion. It is expressed as (3):

$$Th(t) = \frac{D_f(t)}{V_{following}(t)} \quad (3)$$

where a shorter headway signifies increased collision risk due to reduced reaction time. To understand driver behaviour more comprehensively, the acceleration or deceleration, $a(t)$ is derived to observe how rapidly a vehicle adjusts its speed relative to the traffic flow. This is given by (4):

$$a(t) = \frac{[V_{following}(t) - V_{leading}(t)]}{\Delta t} \quad (4)$$

where Δt is the time interval between successive measurements. Positive values indicate acceleration, while negative values represent deceleration; both influence the likelihood of tailgating under dense traffic conditions.

Contextual parameters, such as road type $R(t)$ and traffic density, $TD(t)$ add further interpretability to the data. The road type differentiates between urban and highway segments, each presenting unique traffic patterns and safe driving norms. In contrast, traffic density quantifies the number of vehicles present per unit length of roadway. Alongside these parameters, the instantaneous vehicle speed, $V_s(t)$ represents the speed of the following vehicle at each time step and serves as a fundamental input for calculating dynamic interactions such as braking distance, driver reaction distance, and time headway.

To prepare these features for input into the learning model, continuous variables are normalised to a $[0, 1]$ range to facilitate stable training convergence, and categorical variables such as $R(t)$ are encoded using a one-hot scheme. In addition, lag features are generated to preserve temporal dependencies, which are crucial when modelling sequential driving data.

In a federated learning setup, each participating vehicle operates as an independent client, training its local model without sharing raw data. The final feature vector representing each time step is defined by (5):

$$x_t = [D_f(t), V_r(t), D_b(t), Th(t), V_s(t), R(t), TD(t), a(t)] \quad (5)$$

This vector encapsulates both the dynamic driving characteristics and environmental context necessary for robust tailgating detection. The use of a bidirectional LSTM within the federated framework ensures that both past and future temporal patterns are effectively captured, enabling the system to learn subtle behavioural cues associated with unsafe following behaviour while preserving data privacy.

3.3. Exploratory Dataset Analysis

A detailed analysis of the cleaned SUMO-generated dataset was conducted to examine the key vehicle interaction parameters relevant to unsafe following behaviour. The focus was on understanding the

statistical relationships and distributional characteristics of the selected features to confirm their suitability for subsequent analysis.

The correlation structure, as shown in Figure 3(a), highlights strong and meaningful interdependencies among the core variables. The following distance shows a clear positive association with both braking distance and vehicle speed, indicating that vehicles maintaining larger gaps tend to travel faster and require longer stopping distances. Time headway also shows moderate positive relationships with following distance and braking distance, supporting its established role as a measure of safe vehicle-following intervals. The safety margin is almost perfectly correlated with following distance, demonstrating redundancy and justifying its exclusion as a separate predictor. Notably, the target variable indicating tailgating behaviour exhibits consistently negative correlations with following distance, braking distance, time headway, and vehicle speed. These relationships confirm that reduced spacing, shorter stopping distance, lower headway, and slower speeds are all linked with an increased likelihood of tailgating, aligning well with established traffic safety literature.

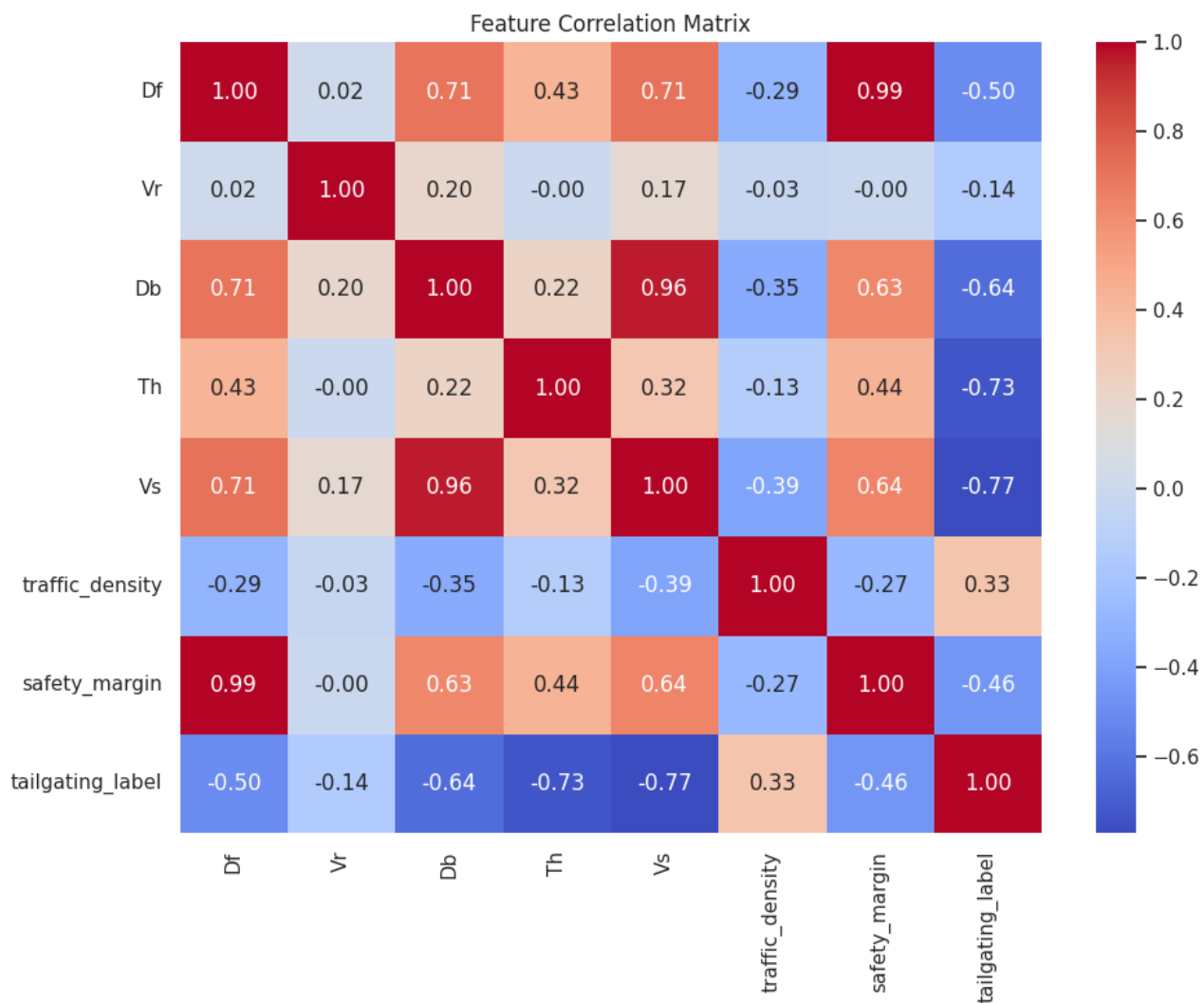


Figure 3(a). Feature correlation heatmap illustrating the relationships between key traffic parameters.

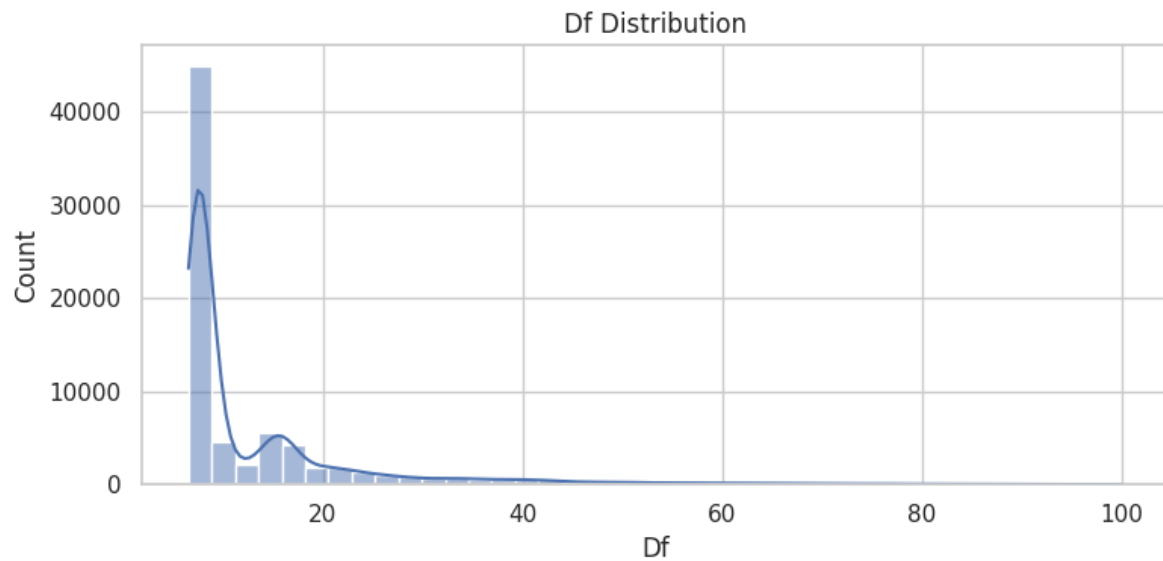


Figure 3(b). Distribution of the following distance across simulated traffic data.

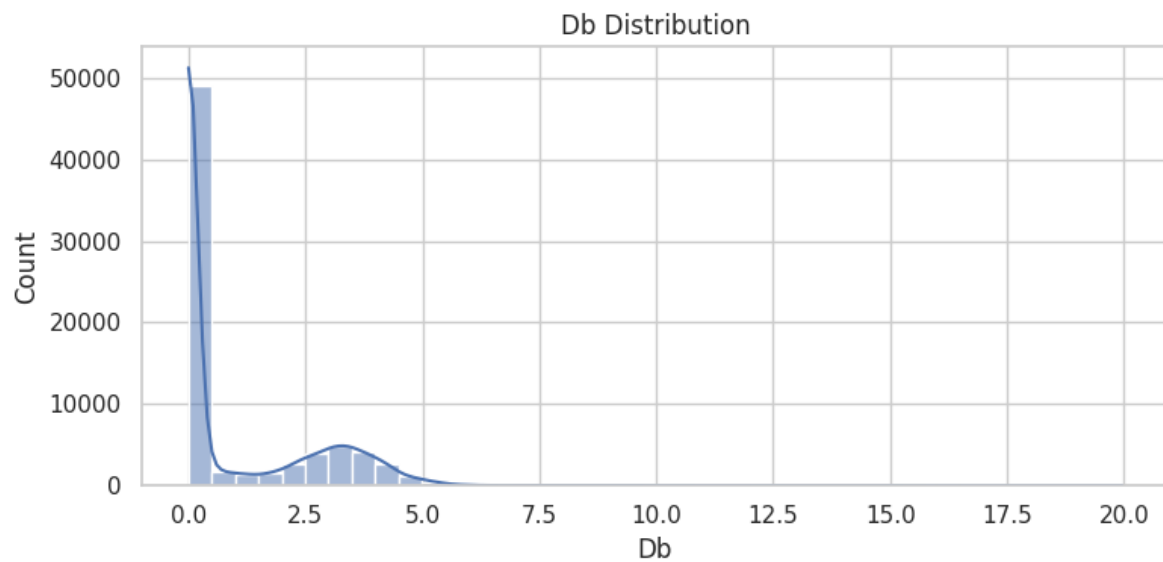


Figure 3(c). Distribution of braking distance under varying vehicle speeds and traffic conditions.

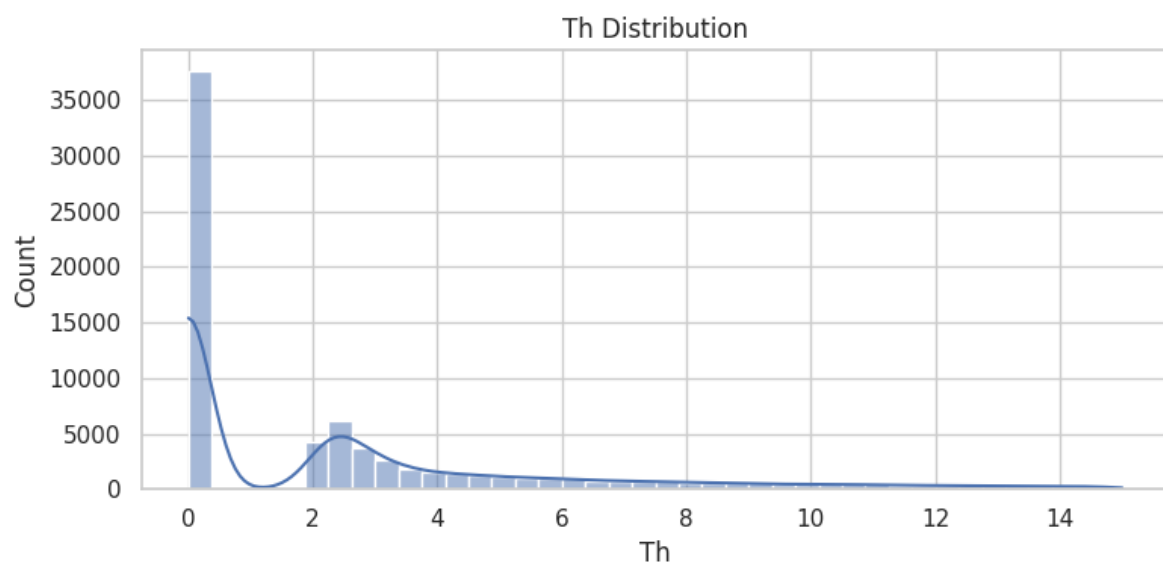


Figure 3(d). Distribution of time headway values indicating safe and unsafe following behaviour.

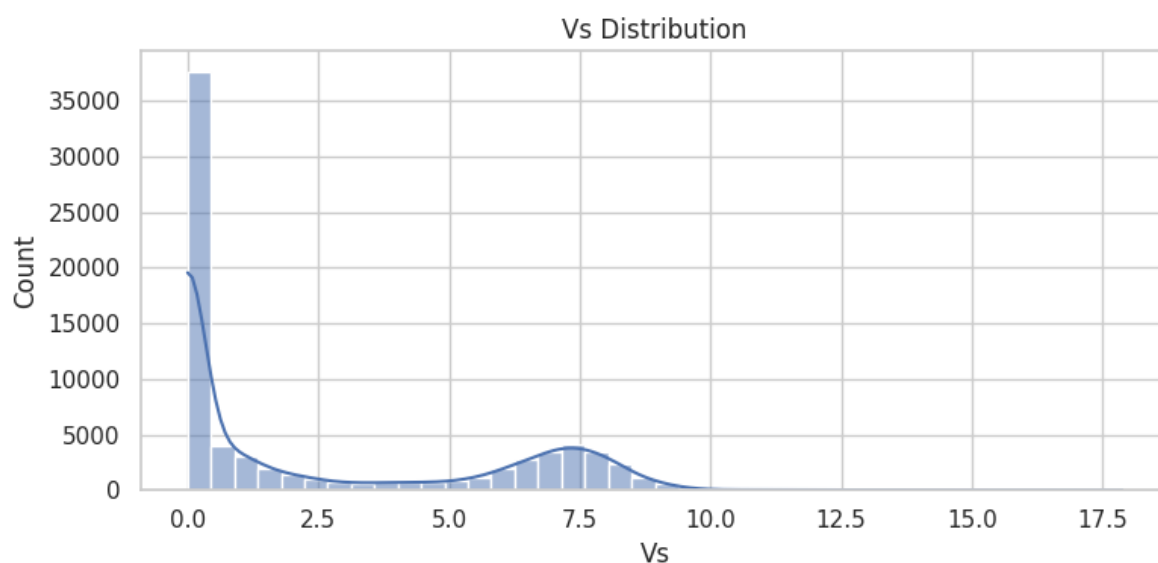


Figure 3(e). Distribution of vehicle speeds across different driving scenarios.

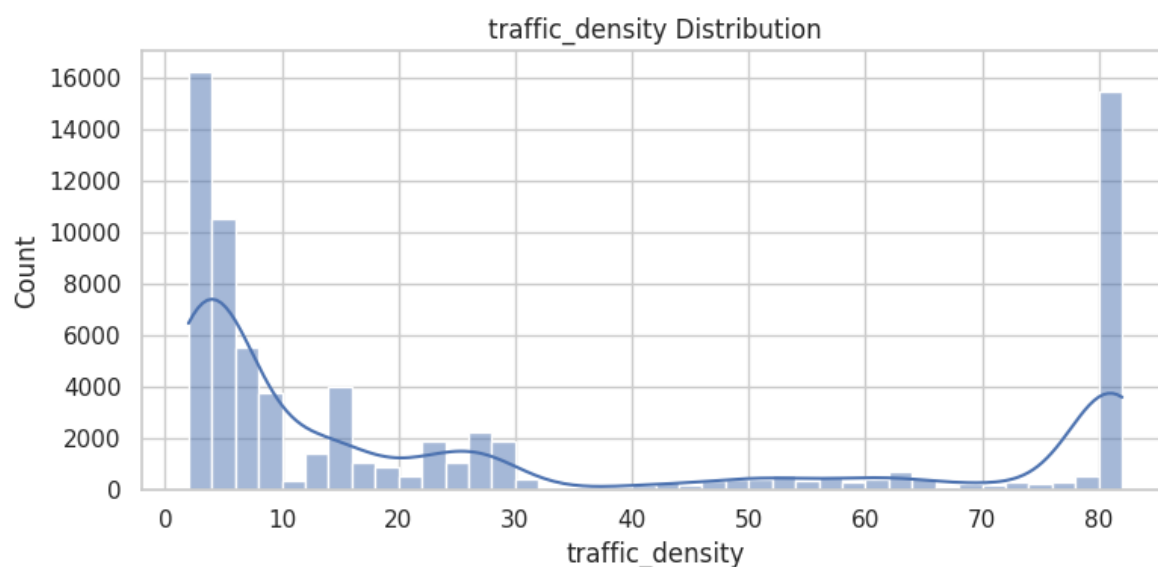


Figure 3(f). Distribution of traffic density reflecting varying congestion levels.

The distributions of the individual variables reinforce these observations. The pattern for the following distance in Figure 3(b) is heavily skewed towards shorter values, revealing that many vehicles in the simulation maintain distances well below recommended safety limits. This tendency highlights a significant prevalence of risky driving conditions in the dataset. The braking distance distribution in Figure 3(c) similarly shows that most vehicles operate within minimal stopping distances, underscoring the potential for unsafe deceleration scenarios, especially in high-density or abrupt braking situations.

The time headway in Figure 3(d) displays a notable concentration of vehicles with intervals shorter than the generally accepted safety thresholds, further indicating that many drivers do not leave adequate space to react to sudden speed changes. The distribution of vehicle speed in Figure 3(e) demonstrates that while a significant portion of vehicles travel at moderate speeds, the presence of a long tail towards higher

speeds suggests realistic coverage of urban and highway segments, where the consequences of tailgating are more severe. The traffic density profile in Figure 3(f) confirms that the dataset captures a wide range of traffic conditions, with distinct peaks at both low and high densities, ensuring that the data represent both free-flow and congested scenarios that can influence car-following behaviour.

Taken together, the correlation patterns and skewed distributions demonstrate that the selected variables, following distance, braking distance, time headway, vehicle speed, and traffic density, capture the conditions that contribute to unsafe following behaviour. This strong representation across diverse driving environments provides a robust basis for further behavioural assessment and predictive modelling.

3.4. FL-based Bi-LSTM Tailgating Detection Model

The framework integrates an FL approach with a Bi-LSTM network to enable privacy-preserving and accurate detection of tailgating behaviour. While various DL models, such as CNN, RNN, and LSTM, have been explored independently for driver behaviour detection, they are typically employed without federated training. In contrast, this work leverages Bi-LSTM within a federated setting, as its architecture is particularly effective for sequential data by capturing both past and future temporal dependencies, thereby improving the detection of tailgating scenarios under dynamic driving conditions.

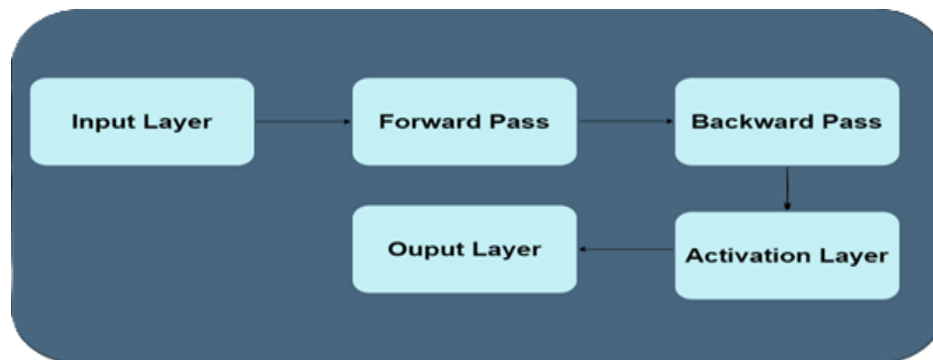


Figure 4. Local training flow of the Bi-LSTM model showing sequential operations including forward pass, backpropagation, activation, and output generation.

In this setup, each participating vehicle operates as an independent FL client. Local Bi-LSTM models are trained using only locally collected driving data. This ensures that raw vehicle data remains decentralised, addressing privacy concerns while still contributing to the overall model performance. The Bi-LSTM network comprises two LSTM layers: one processes the input sequence in the forward temporal direction, while the other processes it in the reverse direction. The hidden states from both directions are concatenated to produce a comprehensive representation of the driving sequence, as shown in (6):

$$h_t = \begin{bmatrix} h_t^{\rightarrow} \\ h_t^{\leftarrow} \end{bmatrix} \quad (6)$$

The model then uses these representations to determine the likelihood of tailgating based on specific safety conditions. First, the time headway condition (7) assesses whether the time headway between two

vehicles is below a critical threshold.

$$Th(t) < Th(t)_{threshold} \quad (7)$$

where $Th(t)$ is the time headway at time t , and $Th(t)_{threshold}$ is typically set to 2 seconds [31]. This condition indicates insufficient reaction time for the following vehicle to avoid a rear-end collision.

Second, the safety margin condition (8) checks whether the available following distance $D_f(t)$ is greater than the computed safe stopping distance $D'_s(t)$:

$$SafetyMargin = D_f(t) - D'_s(t) \quad (8)$$

If this margin is negative, it indicates that the vehicle does not have enough distance to stop safely, implying tailgating behaviour. The safe stopping distance, $D'_s(t)$ is computed by summing the driver reaction distance and braking distance, adjusted for additional motion. The driver's reaction distance is given by (9):

$$D_r = V_s(t) * t_r \quad (9)$$

where $V_s(t)$ is the vehicle's speed and t_r is the average driver reaction time, considered to be 1.5 seconds, as per the Federal Highway Administration Guidelines. The total stopping distance is calculated as in (10):

$$D_s = D_r + D_b(t) \quad (10)$$

Finally, the safe stopping distance adds a term to account for the vehicle's relative motion as shown in (11):

$$D'_s(t) = D_s + \frac{V_{following}(t)^2}{2a_{max}} \quad (11)$$

where $V_{following}(t)$ is the relative speed and $a_{\{max\}}$ is the maximum deceleration capacity. A vehicle is classified as tailgating if either the time headway condition or the safety margin condition indicates unsafe following. The binary indicator for tailgating is defined as in (12):

$$T = \begin{cases} 1, & \text{if } Th(t) < Th(t)_{threshold} \\ 0, & \text{otherwise} \end{cases} \quad \text{or } SafetyMargin < 0 \quad (12)$$

For training the global model in the FL setup, each client updates its local model parameters using stochastic gradient descent (SGD). The weight update rule is given by (13):

$$\omega_{t+1} = \omega_t - \eta \nabla L(\omega_t) \quad (13)$$

where ω_t represents the model weights at iteration t , η is the learning rate, and $\nabla L(\omega_t)$ is the loss function. Local model updates are aggregated on the central server using the Federated Averaging Algorithm (14):

$$W_{global} = \frac{1}{N} \sum_{i=1}^N \frac{\omega_i * n_i}{\sum_{j=1}^N n_j} \quad (14)$$

where W_{global} represents the updated global model weights, ω_i are the local model weights from the i -

th vehicle, n_i is the number of data points in the i -th vehicle's dataset, and N is the total number of vehicles.

The goal is to learn a single global model, $J(\omega)$, from the data collected across participating vehicles, where D_k denotes each vehicle's dataset and the local training dataset size $D = \sum_{k=1}^K D_k$. Considering a set of input-output pairs $\{x_i, y_i\}_{i=1}^{D_k}$ where $x_i \in R^d$ represents the feature vector, and $y_i \in \{0,1\}$ represents the label indicating tailgating behaviour; The local loss function for the k^{th} vehicle is defined in (15):

$$J_k(\omega) := \frac{1}{D_k} \sum_{i \in D_k} f_i(\omega) + \lambda h(\omega). \quad (15)$$

where $f_i(\omega)$ is the reconstruction loss for each data point, and $h(\omega)$ is a regularisation term to reduce overfitting. The global loss function aggregates all local losses as shown in (16):

$$J(\omega) = \sum_{k=1}^K \frac{H_k}{D} J_k(\omega) \quad (16)$$

This process enables us to collaboratively train an FL-based Bi-LSTM DL model, as outlined in Algorithm 1 of the tailgating approach, while keeping the data of each vehicle. After completing all the rounds, return the final model parameters and the loss value. The novelty of the developed framework lies in integrating a privacy-preserving federated learning strategy with a bidirectional LSTM network for tailgating detection in realistic driving environments. Unlike conventional centralised DL approaches, this framework enables multiple vehicles to collaboratively train a shared model without exchanging raw trajectory data. This design protects sensitive driver information while capturing the full temporal dynamics of vehicle-following behaviour in both directions. The workflow diagram shown in Figure 4 highlights how local Bi-LSTM models are trained independently at the vehicle level, with only model updates shared for aggregation at the central server. This approach ensures that data privacy, scalability, and real-time applicability are all addressed simultaneously, demonstrating a practical solution for ITS.

3.5. Experimental Setup and Implementation Details

Table 1 summarises the main experimental parameters and hyperparameters to ensure clarity and reproducibility. These include key simulation settings, model configurations, hardware and software specifications, and the baseline models used for comparative evaluation. The SUMO-generated dataset, although custom-developed, was created using standard open-source tools with fully documented simulation scenarios, making the framework reproducible for other researchers. To maintain consistency, the same dataset, pre-processing pipeline, and federated learning configuration were applied across all four DL models: CNN, RNN, LSTM, and the presented Bi-LSTM. The CNN and RNN models serve as baseline architectures for non-sequential and basic sequential pattern recognition tasks, while the LSTM provides a unidirectional sequence learning baseline.

The Bi-LSTM extends this by capturing both past and future temporal dependencies, which is

essential for modelling dynamic vehicle interactions in real-world traffic scenarios. Each model was trained under a consistent set of hyperparameters, including learning rate, batch size, optimiser, and training split ratio. For the federated learning setup, each local client performed multiple local training epochs per round, and the system ran for multiple global communication rounds until the global model converged. Specifically, the experiments used a 70% training and 30% testing split, with five local epochs per round and five global rounds, providing a balanced trade-off between model accuracy and computational efficiency.

Algorithm 1. Federated learning-based Bi-LSTM training process for privacy-preserving tailgating detection using decentralised vehicle trajectory data.

Input:

- V: Set of all participating vehicles.
- X, Y: Input features and labels.
- H: Initial hidden states of the Bi-LSTM.
- Mini-batch size (m), number of iterations (n), learning rate (α).
- Optimiser: SGD.

Output:

- Final loss value $J(\omega)$
- Updated model weights ω
- Forward, backward, and output weights for the Bi-LSTM: W_f, W_b, W_o .

Begin:

1. Initialise global model: Initialise the cloud model with parameters: $J, \omega_0, W_f^0, W_b^0, W_o^0, H_0$.
2. Federated learning rounds: For each training round $i=1, 2, 3, \dots, n$. Select participating vehicles $V_i \subset V$ for this round.
3. Local Training at Each Vehicle:
 - For each vehicle $v \in V_i$:
 - 3.1. Initialise local model: Initialise a local copy of the global Bi-LSTM model for vehicle v .
 - 3.2. Prepare input data: Use local feature sequences for time steps $[D_f(t), V_r(t), D_b(t), Th(t), V_s(t), R(t), TD(t), a(t)]$ from the vehicle's data.
 - 3.3. Train the Bi-LSTM Model:
 - Forward pass: Calculate cell states and hidden states using forward (h_t^f) and (h_t^b) backward passes.
 - Calculate gradients: Perform backpropagation to calculate gradients $\nabla L(\omega_t)$ for model parameters.
 - Update local weights: Update the weights using the optimiser: $\omega_{t+1}^v = \omega_t^v - \alpha \cdot \nabla L(\omega_t^v)$
4. Aggregation at Central Server:
 - 4.1. Collect local updates: Receive updated weights from all participating vehicles.
 - 4.2. Aggregate weights (Federated Averaging): Update the global model by aggregating the local weights: $\sum_{v=1}^N \frac{\omega_t^v}{N}$

Where N is the number of participating vehicles.
5. Update global model: Update global parameters (ω, W_f, W_b, W_o .)
6. Return final output.

Table 1. Comparison of training hyperparameters and experimental configurations for CNN, RNN, LSTM, and FL-Bi-LSTM models.

Item	Details
Simulation Tool	SUMO (open-source, custom scenarios)
Total Data Samples	~100,000
Train/Test Split	70% training, 30% testing
Number of Local Clients	5 vehicles
Models Trained	CNN, RNN, LSTM, Bi-LSTM (non-FL and FL)
History Window Length	10 time steps
Hidden Layers	1–3 (grid search)
Units per Hidden Layer	50, 100, 150 (grid search)
Optimizer	SGD (stochastic gradient descent)
Learning Rate (η)	0.001
Batch Size	32
Aggregation Method	Federated average
Local Epochs per Round	5
Number of FL rounds	5
Hardware Used	CPU: Intel i7; GPU: NVIDIA RTX 3070; 16 GB RAM
Software	TensorFlow Federated (TFF) on Ubuntu 20.04
Dataset Accessibility	Custom SUMO dataset, reproducible by others

4. Experimental Result

In this study, the performance of the FL–Bi-LSTM model was compared with CNN [6], RNN [17], and LSTM [27] under both FL and non-FL settings, using identical simulation configurations. Prior non-FL implementations, such as LSTM for tailgating detection [31] and CNN for rear-end collision driver behaviour analysis [6], were used for reference to contextualise improvements gained through the federated approach. The primary goal was to evaluate the impact of FL on model performance while preserving data privacy in detecting unsafe following behaviour.

Each model's performance was assessed using Accuracy, Precision, Recall, F1-Score, Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The results are summarised in Table 2. The Bi-LSTM model, when trained with FL, achieved an accuracy of 0.9198, compared to 0.8844 for non-FL, demonstrating the benefit of federated training in enhancing predictive accuracy while keeping the data decentralised. Precision also improved from 0.5228 (non-FL) to 0.7856 (FL), highlighting the model's enhanced ability to identify valid positive instances of tailgating.

Table 2. Comparative performance metrics for CNN, RNN, LSTM, and Bi-LSTM models under FL and non-FL configurations.

	Model	CNN [6]	RNN [17]	LSTM [31]	Bi-LSTM (This framework)
Accuracy	non-FL	0.86180	0.8145	0.8087	0.8844
	FL	0.88077	0.8648	0.8898	0.9198
Precision	non-FL	0.7222	0.4605	0.447	0.5228
	FL	0.7554	0.735	0.685	0.7856
F1-Score	non- FL	0.5473	0.5086	0.4953	0.5902
	FL	0.6282	0.5865	0.5574	0.6815
Recall	non- FL	0.6031	0.5678	0.555	0.6047
	FL	0.6824	0.6517	0.6015	0.6853
MSE	non- FL	0.2250	0.1820	0.1550	0.1480
	FL	0.1912	0.0850	0.0780	0.0650
RMSE	non- FL	0.3536	0.3767	0.3930	0.3240
	FL	0.3120	0.2910	0.2790	0.2550

Table 3. Comparative Analysis of FL-Bi-LSTM Tailgating Detection Framework with Baseline Literature Approaches

Model	Reference	Accuracy (%)	Parameters Considered	FL
CNN	[6]	87.6	Acceleration, speed, RPM, and gravity.	×
RNN	[17]	89.6 (from ADE 1.249 ft)	X and Y position, speed, heading	×
LSTM	[31]	60.67	Time series dependencies	×
Bi-LSTM	This framework	91.98	Following distance, relative speed, braking distance, time headway, vehicle speed, road type, traffic density, acceleration	✓

For the CNN model [6], accuracy improved from 0.8618 (non-FL) to 0.8808 (FL). Precision increased slightly from 0.7222 to 0.7554, confirming that federated training supports better generalisation without compromising specificity. The RNN model [17] demonstrated a substantial accuracy gain, increasing from 0.8145 to 0.8648 under FL, with a corresponding rise in Precision to 0.7350. Although Recall dropped slightly, this indicates a more conservative prediction. The LSTM model [31] under FL achieved an accuracy of 0.8898, up from 0.8087 in non-FL, with Precision rising from 0.4470 to 0.6850. These improvements demonstrate the consistent benefit of decentralised learning for all architectures.

Table 3 presents a clear comparison of the FL-Bi-LSTM framework with existing methods in the literature. This table summarises the key performance metrics, the parameters considered, and whether each

method uses federated learning. The results show that the FL–Bi-LSTM model achieves higher detection accuracy while capturing realistic driving behaviours such as following distance, relative speed, braking distance, and time headway. Unlike conventional centralised models, the FL–Bi-LSTM maintains data privacy by training collaboratively without sharing raw driving data. This comparison highlights the practical benefits and improved effectiveness of the FL–Bi-LSTM framework for real-world ITS.

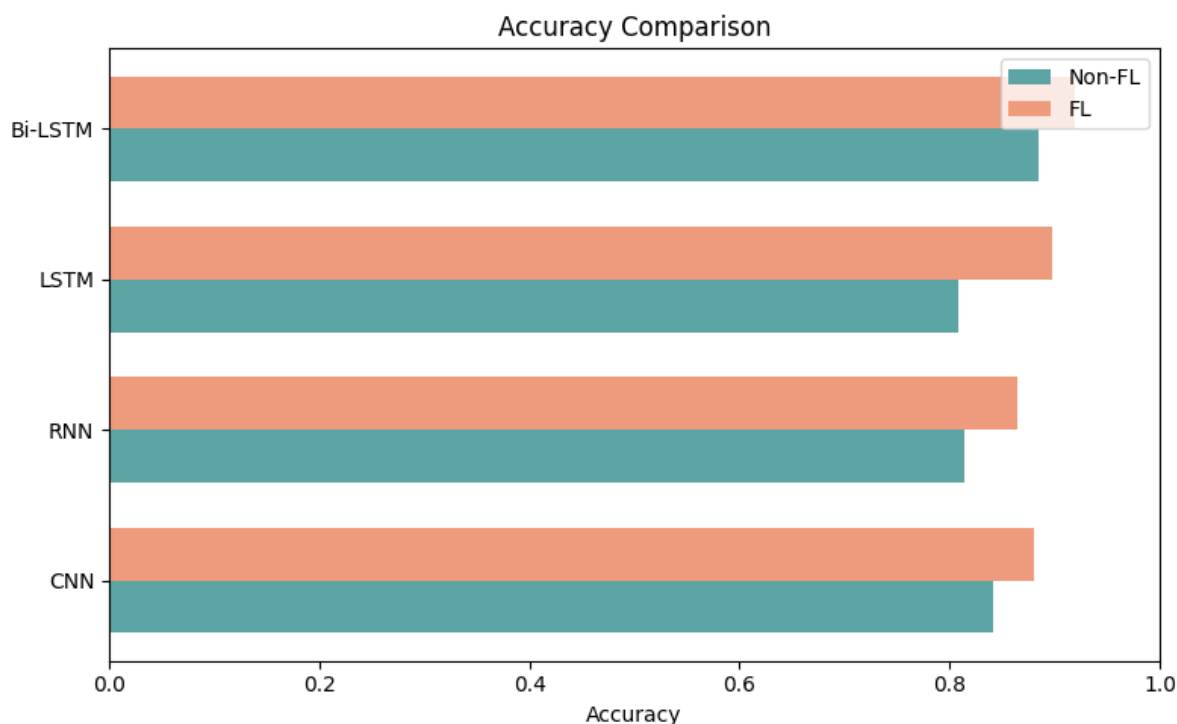


Figure 5(a). AUC Comparison: non-FL vs FL for CNN, RNN, LSTM, and Bi-LSTM.

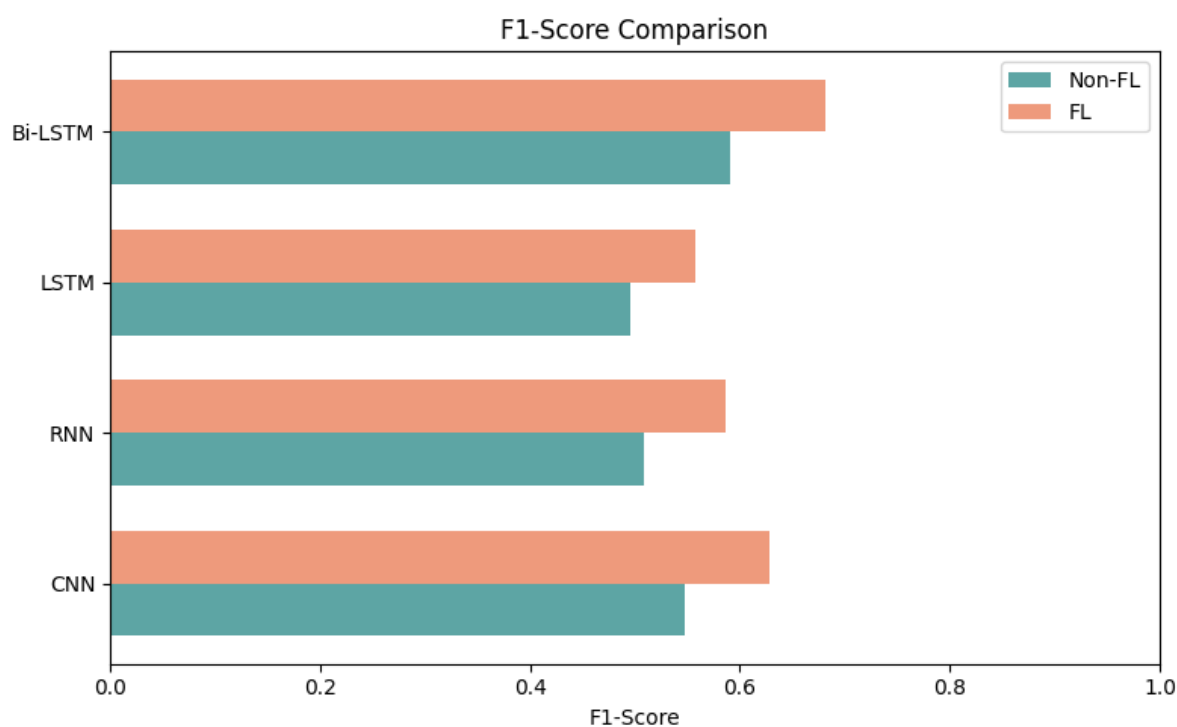


Figure 5(b). F1-Score Comparison: non-FL vs FL for CNN, RNN, LSTM, and Bi-LSTM.

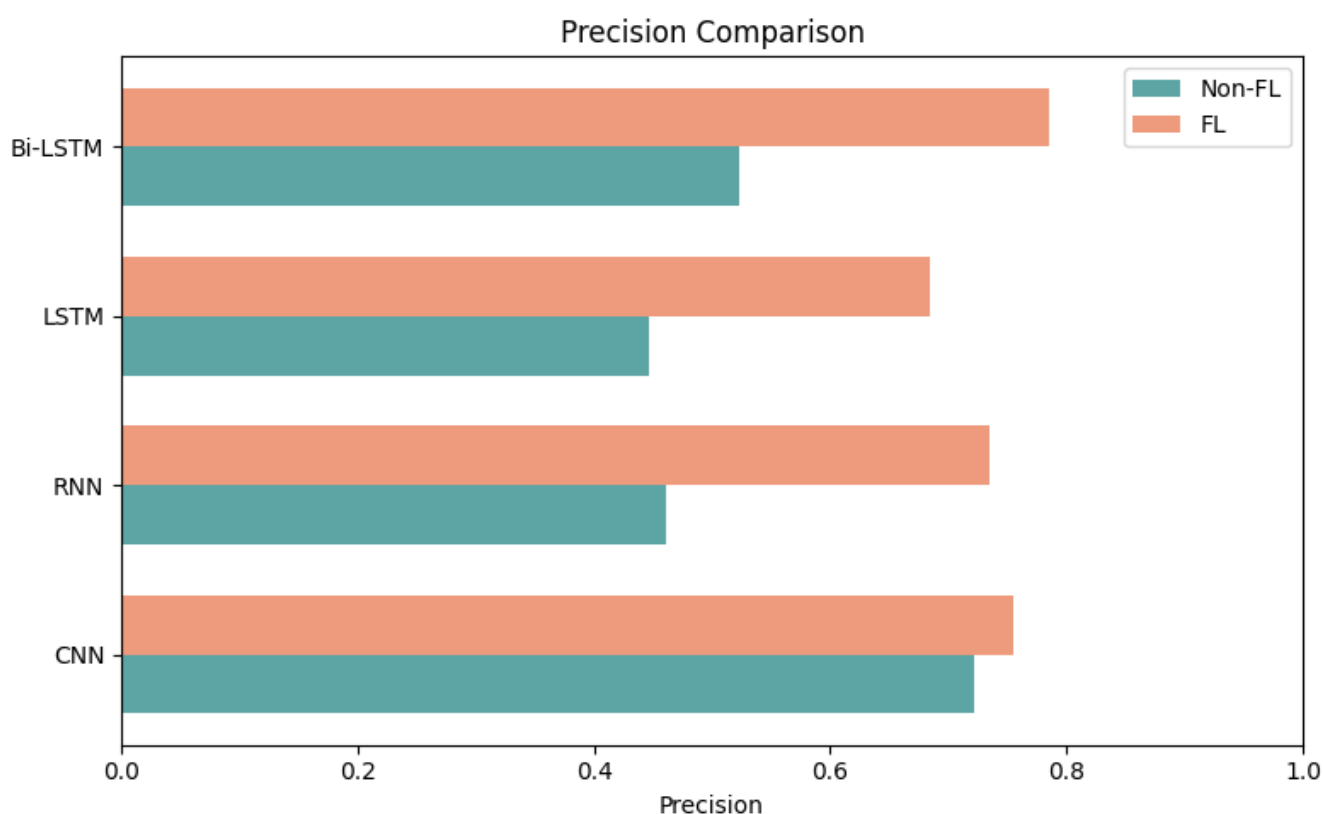


Figure 5(c). Precision Comparison: non-FL vs FL for CNN, RNN, LSTM, and Bi-LSTM.

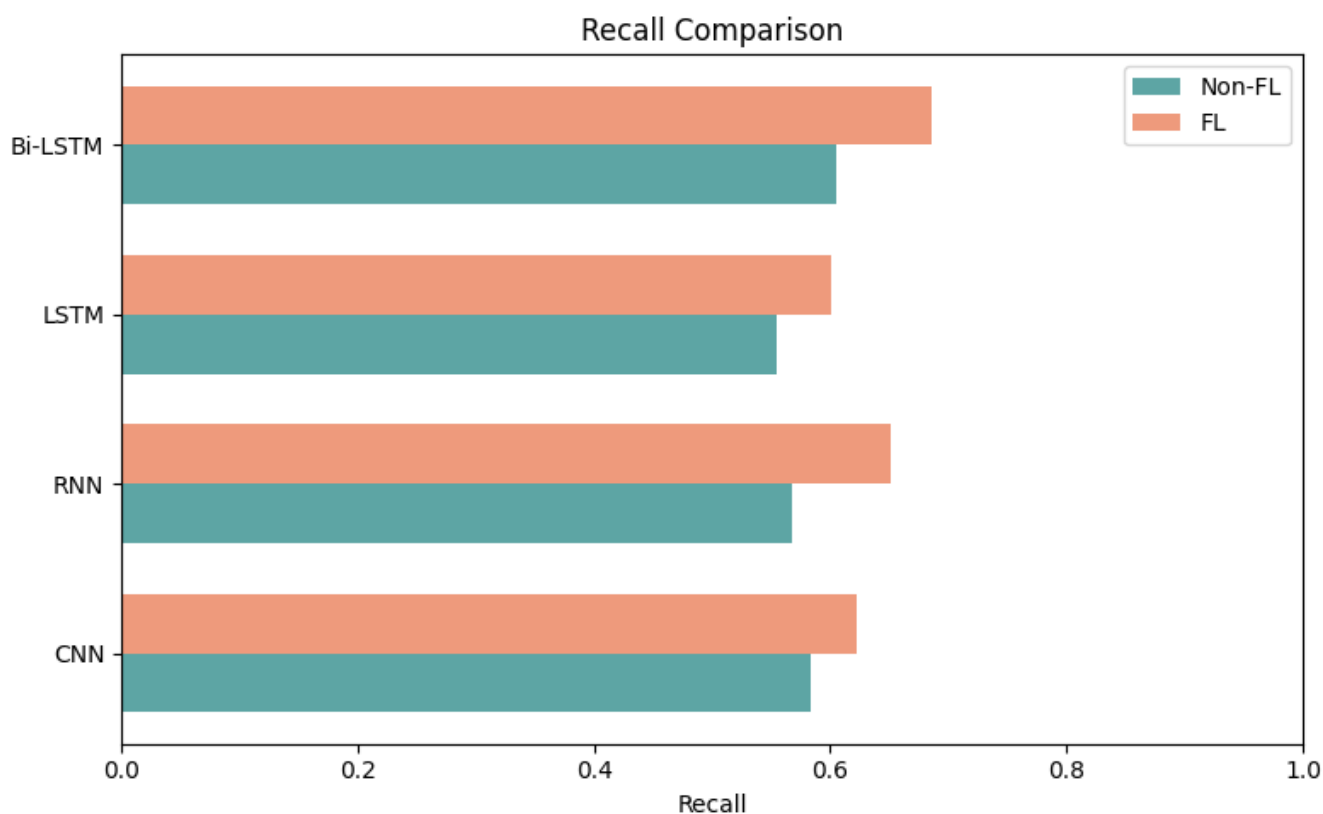


Figure 5(d). Recall Comparison: non-FL vs FL for CNN, RNN, LSTM, and Bi-LSTM.

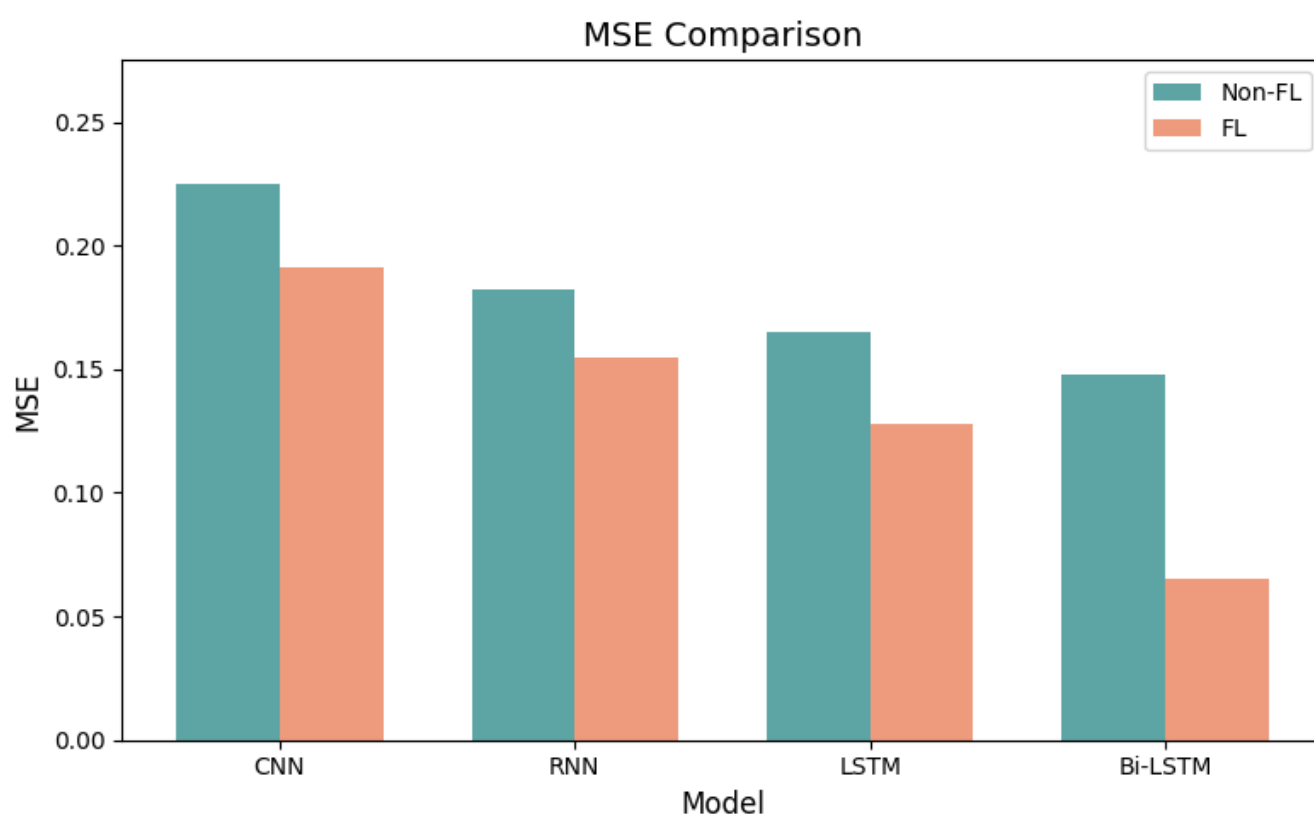


Figure 5(e). MSE Comparison: non-FL vs FL for CNN, RNN, LSTM, and Bi-LSTM.

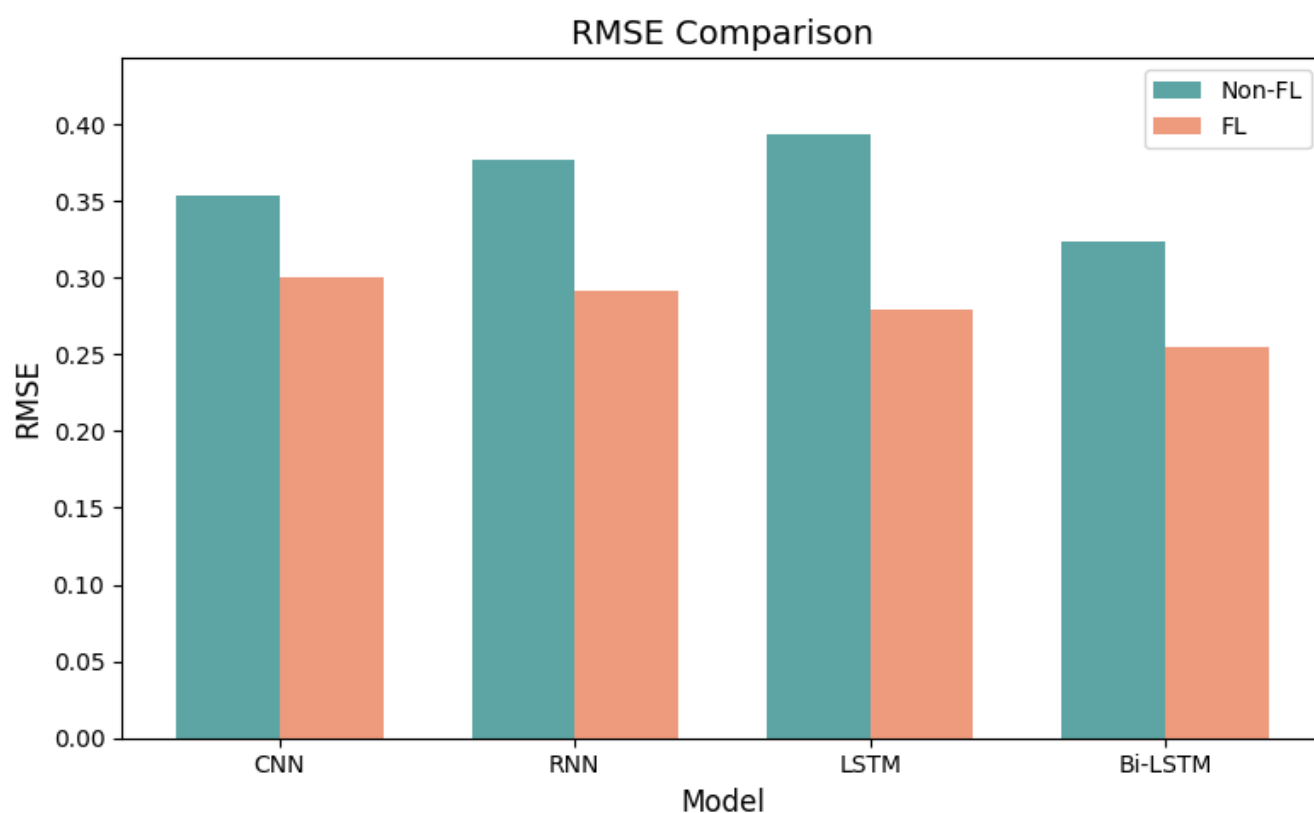


Figure 5(f). RMSE Comparison: non-FL vs FL for CNN, RNN, LSTM, and Bi-LSTM.

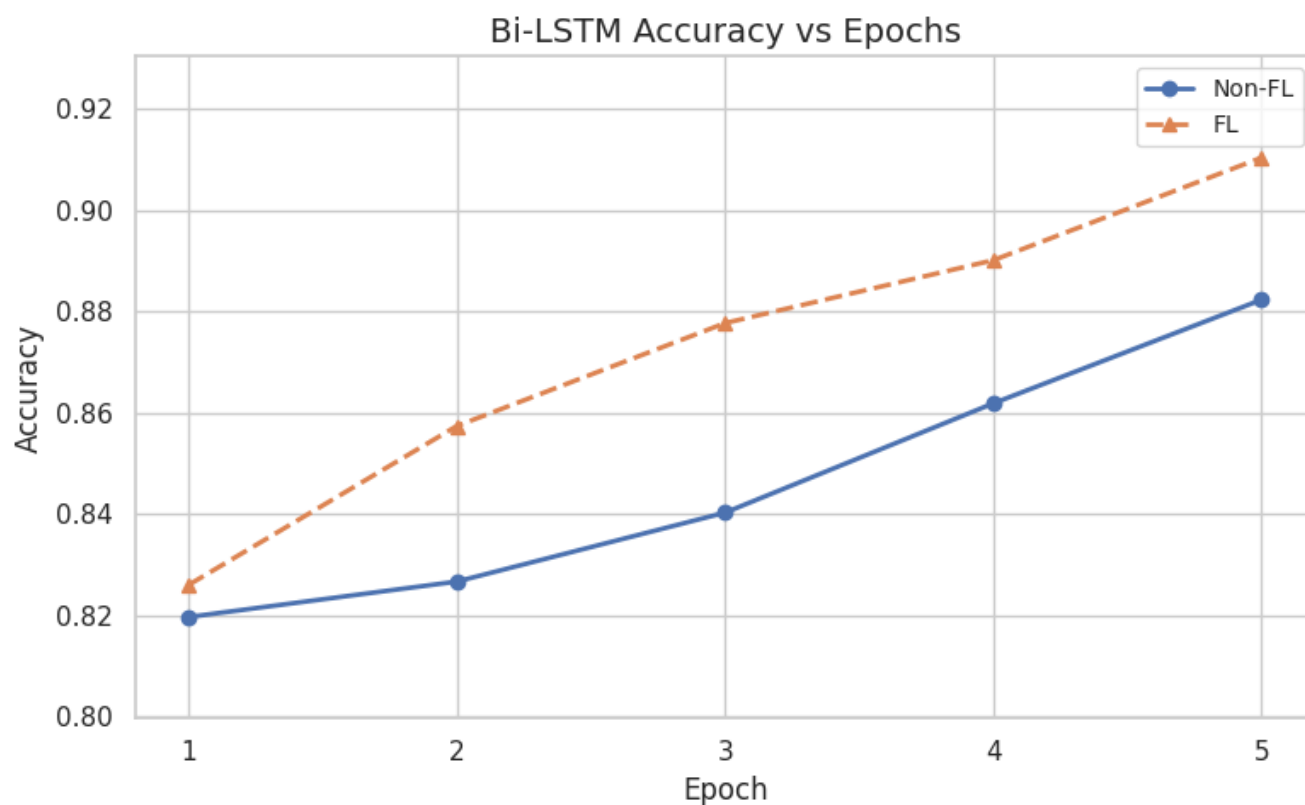


Figure 6(a). Comparison of Bi-LSTM model accuracy across epochs for FL and non-FL settings.

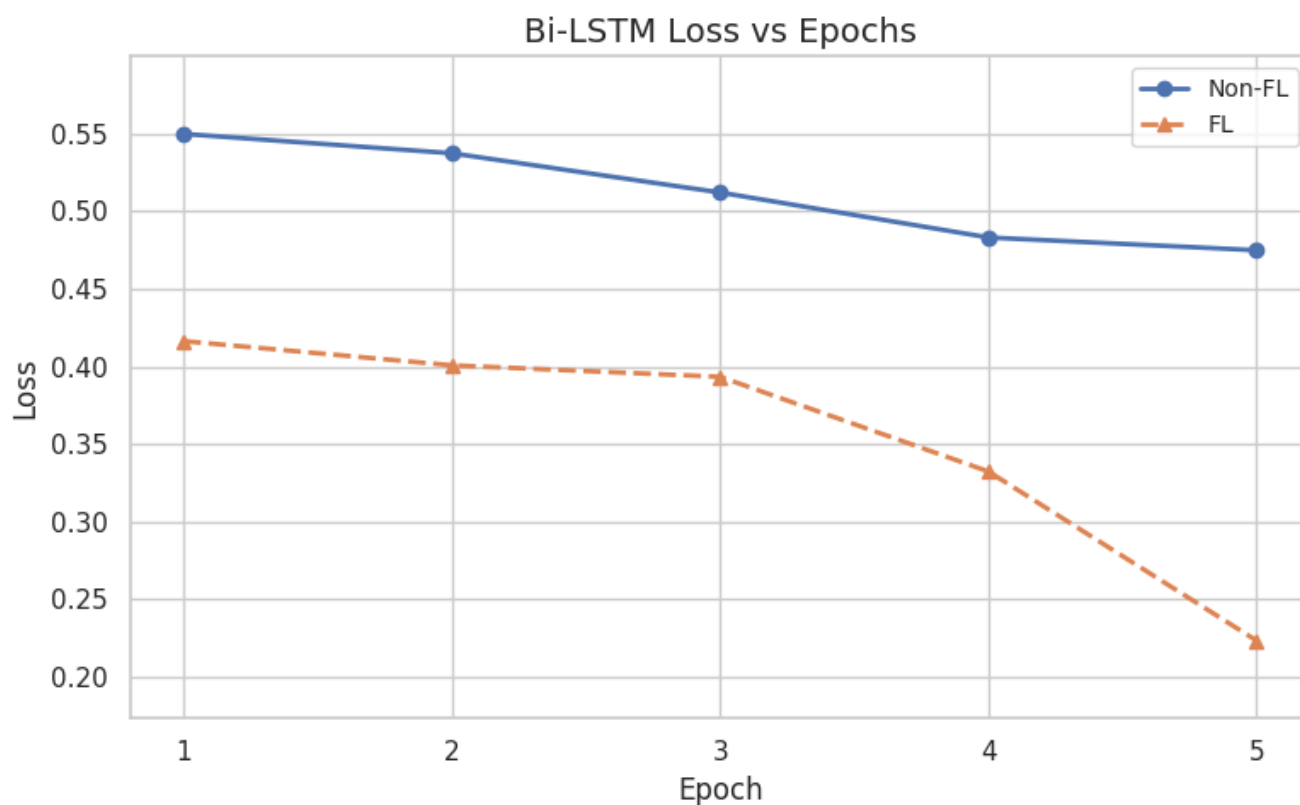


Figure 6(b). Bi-LSTM model loss over epochs comparing FL and non-FL training approaches.

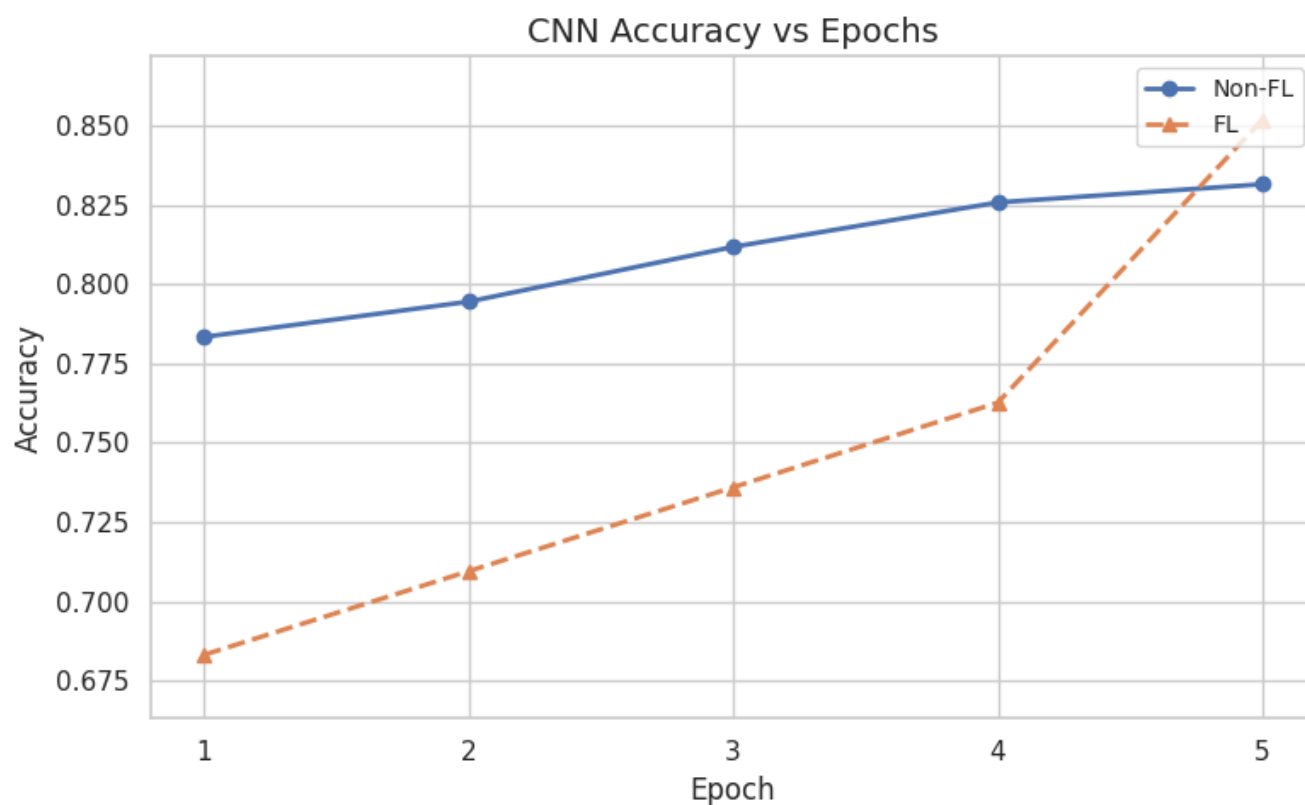


Figure 7(a). CNN model accuracy across epochs for both FL and non-FL training settings.

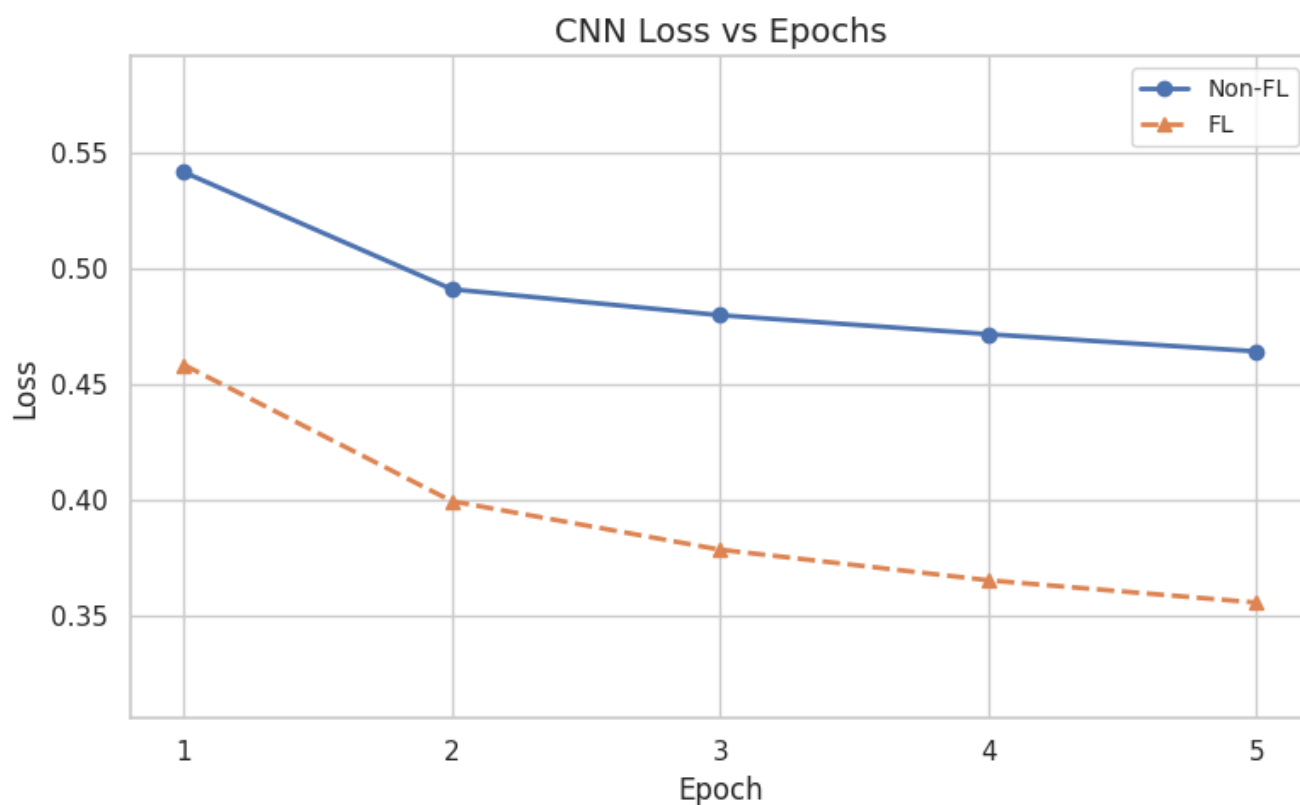


Figure 7(b). CNN model loss across epochs for both FL and non-FL training configurations.

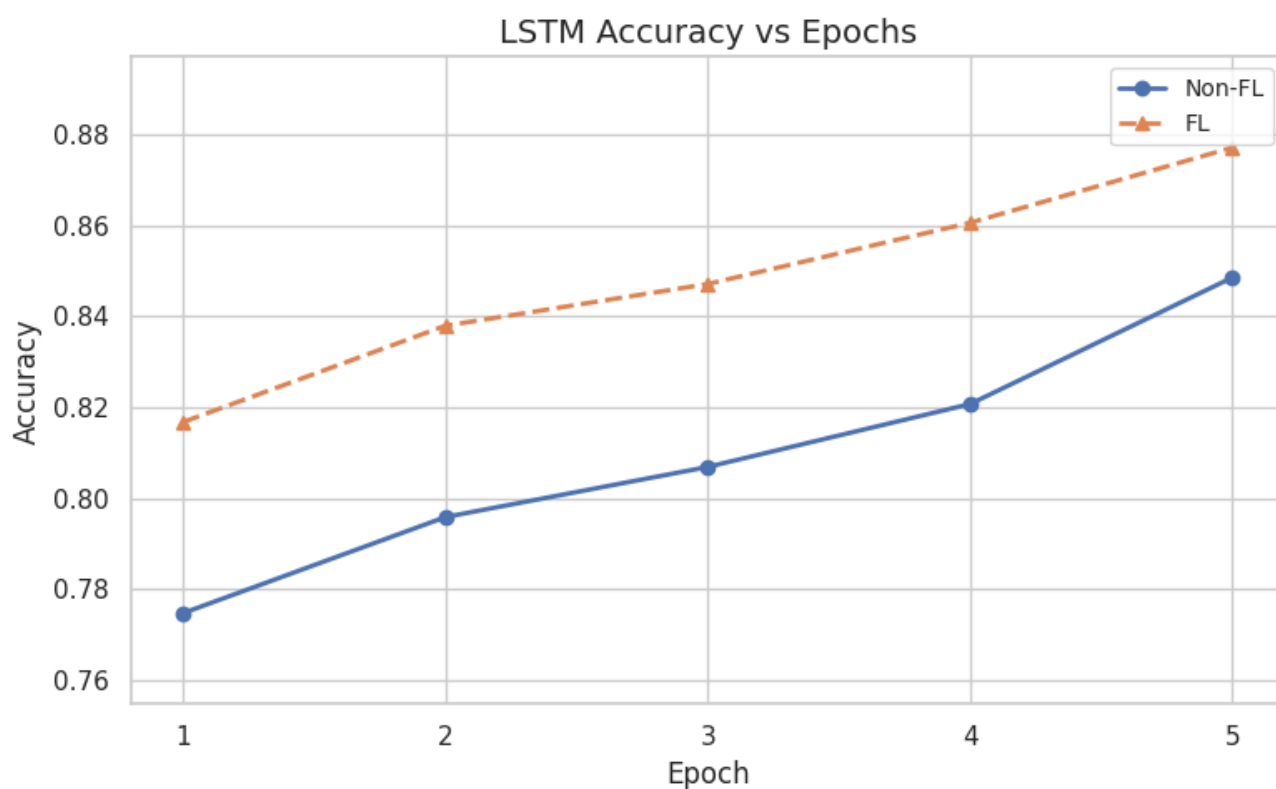


Figure 8(a). LSTM model accuracy over training epochs, comparing federated and non-federated learning setups.

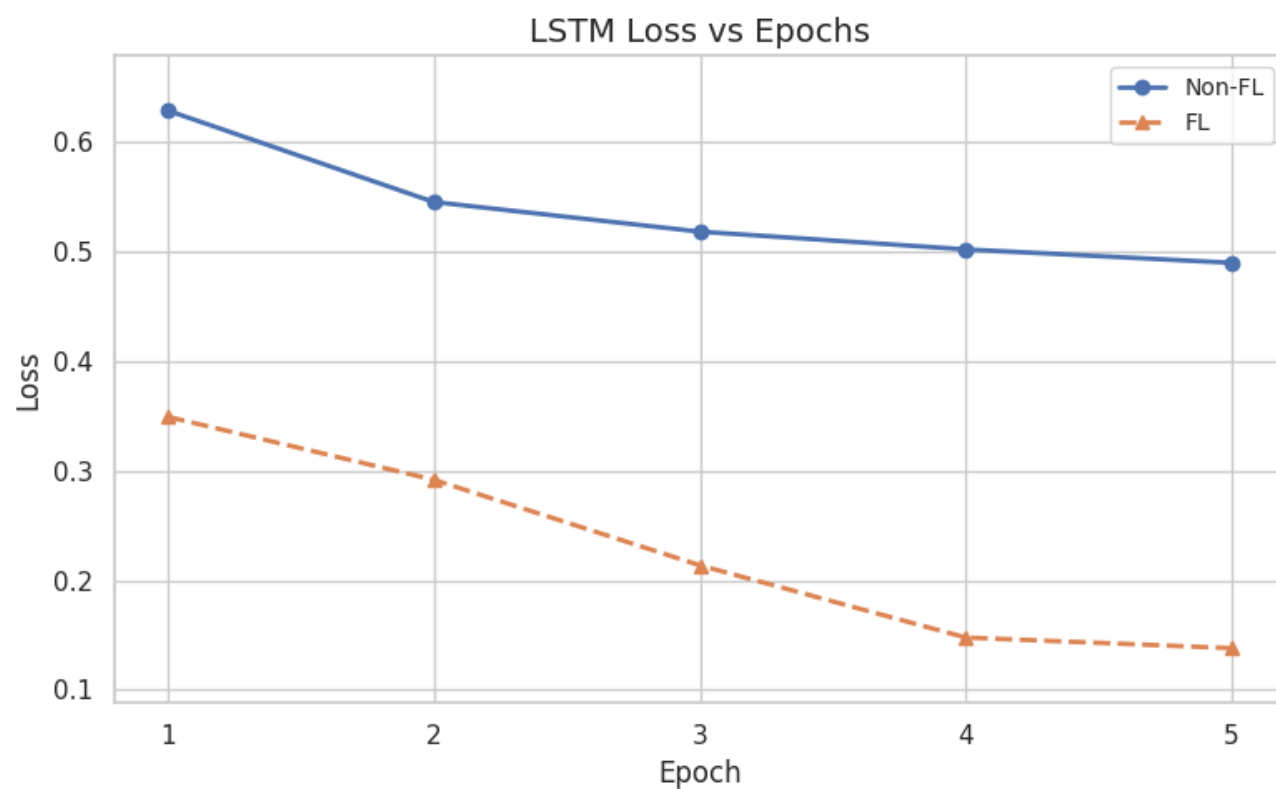


Figure 8(b). LSTM model loss over training epochs, illustrating performance in both federated and non-federated learning configurations.

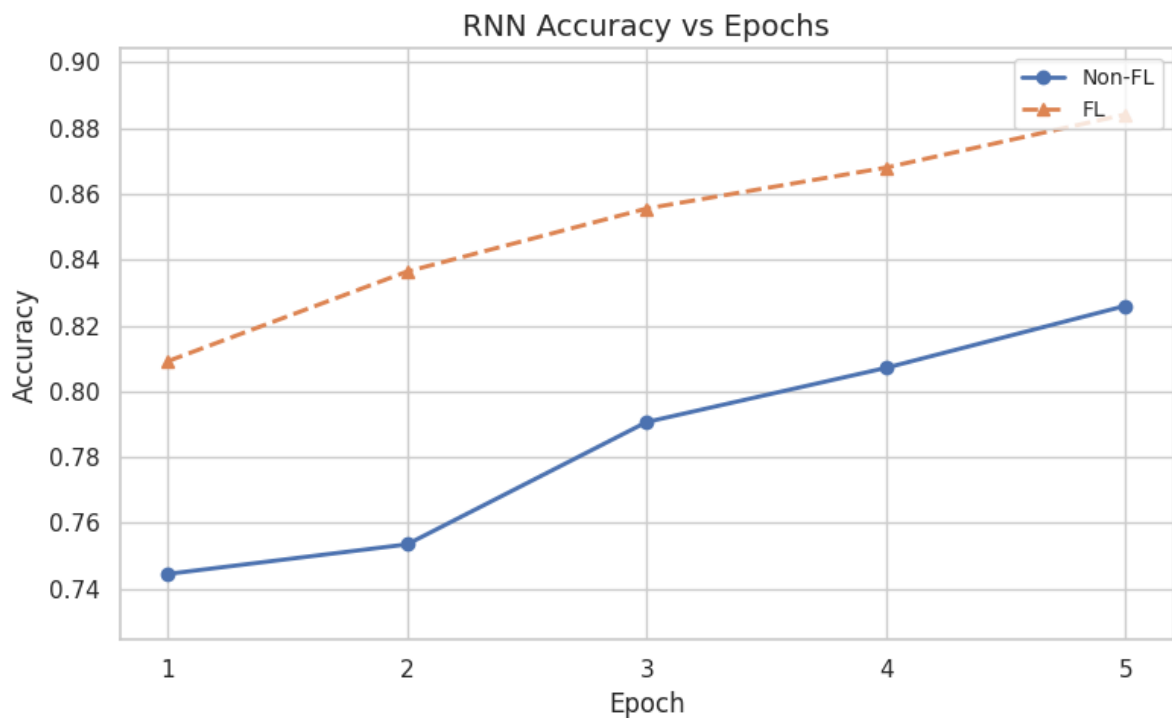


Figure 9(a). RNN model accuracy across training epochs, comparing federated and non-federated learning setups.

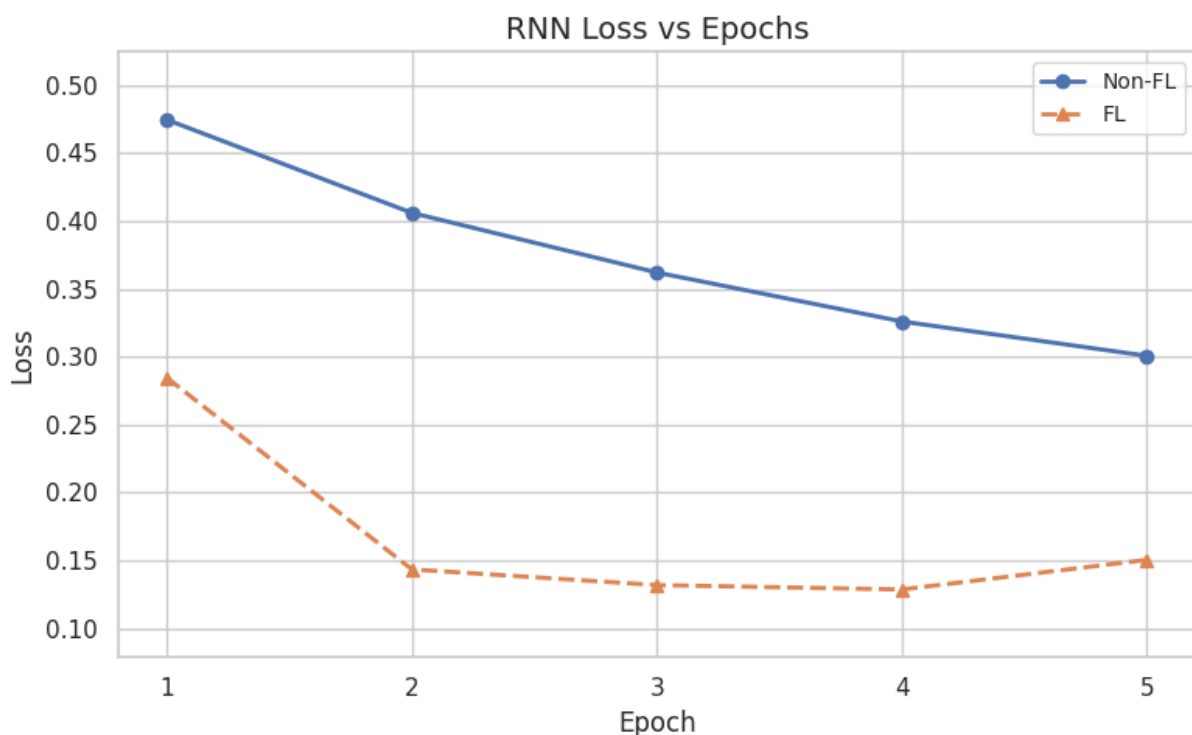


Figure 9(b). RNN model loss across training epochs under both federated and non-federated learning schemes.

Figures 5(a)–5(f) present the comparative performance metrics for each model under FL and non-FL settings. Specifically, they illustrate the AUC, F1-Score, Precision, Recall, MSE, and RMSE, respectively. These visual comparisons demonstrate that the federated approach consistently outperforms the centralised

baseline across all measures, resulting in lower prediction errors and greater robustness.

Figures 6–9 illustrate the accuracy and loss trends over multiple training epochs for each DL model. Figures 6(a) and 6(b) show the Bi-LSTM model's accuracy and loss under FL and non-FL configurations. Similarly, Figures 7(a) and 7(b) present these trends for the CNN model, Figures 8(a) and 8(b) for the LSTM, and Figures 9(a) and 9(b) for the RNN. Across all models, the FL-trained versions consistently demonstrate better stability, faster convergence, and lower loss compared to their non-FL counterparts. The RNN model shows the most significant improvement in early-stage learning, achieving faster accuracy gains under FL.

Overall, these results confirm that the FL-Bi-LSTM framework provides a robust solution for detecting unsafe following behaviour while maintaining data privacy. The bidirectional design allows the model to capture both past and future temporal dependencies, which is crucial for modelling complex driving patterns. The consistent improvement in accuracy and precision across all tested models, with only minor trade-offs in recall for some configurations, underscores the practical value of FL for real-world ITS deployments.

5. Conclusion and Future Work

This study demonstrates the viability of a privacy-preserving FL framework integrating a Bi-LSTM model for tailgating detection in realistic traffic scenarios using synthetic vehicle trajectory data generated by SUMO. The FL-Bi-LSTM achieved an Accuracy of 91.98% compared to 79.44% for the non-FL setting, with improved Precision (0.67), F1 (0.62), and reduced MSE (0.0775) and RMSE (0.2784), confirming its superior performance over conventional models such as CNN, RNN, and LSTM, while ensuring that sensitive data remains decentralised. Although the current framework relies on simulation-based data, which cannot fully capture the unpredictability and noise inherent in real-world driving conditions, it provides a strong foundation for future work. Practical deployment will require addressing challenges such as low-latency federated updates, minimising computational overhead on edge devices, and integrating the framework within diverse ITS infrastructures. The adoption of emerging communication technologies such as 5G can help reduce latency and enhance real-time parameter exchange. Future research will focus on validating the framework with real-world vehicular data, optimising model compression, ensuring secure communication, and developing adaptive learning strategies to enable large-scale, real-time deployment in next generation ITS applications.

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References

- [1] Ministry of Road Transport and Highways, "Road Accidents in India", New Delhi, India, 2022.
- [2] Y. Lin, P. Wang, and M. Ma, "Intelligent Transportation System(ITS): Concept, Challenge and Opportunity," in *2017 IEEE 3rd International Conference on Big Data Security on Cloud (BigDataSecurity), IEEE International Conference on High Performance and Smart Computing, (HPSC) and IEEE International Conference on Intelligent Data and Security (IDS)*, 2017: IEEE Computer Society, pp. 167-172, doi: <https://doi.org/10.1109/BigDataSecurity.2017.50>.
- [3] T. Li, A. K. Sahu, A. Talwalkar, and V. Smith, "Federated Learning: Challenges, Methods, and Future Directions," *IEEE Signal Processing Magazine*, vol. 37, no. 3, pp. 50-60, 2020, doi: <https://doi.org/10.1109/msp.2020.2975749>.
- [4] Q. Li et al., "A Survey on Federated Learning Systems: Vision, Hype and Reality for Data Privacy and Protection," *IEEE Transactions on Knowledge and Data Engineering*, vol. 35, no. 4, pp. 3347-3366, 2023, doi: <https://doi.org/10.1109/TKDE.2021.3124599>.
- [5] S. Ucar, R. Mercer, and E. Keogh, "Tailgating Behavior Detection On Rear Vehicles," in *2023 IEEE 26th International Conference on Intelligent Transportation Systems (ITSC)*, 2023 2023, pp. 440-445, doi: <https://doi.org/10.1109/ITSC57777.2023.10421789>.
- [6] M. Shahverdy, M. Fathy, R. Berangi, and M. Sabokrou, "Driver behavior detection and classification using deep convolutional neural networks," *Expert Systems with Applications*, vol. 149, p. 113240, 2020, doi: <https://doi.org/10.1016/j.eswa.2020.113240>.
- [7] K. Bylykbashi, E. Qafzezi, P. Ampirit, M. Ikeda, K. Matsuo, and L. Barolli, "A Fuzzy Logic Approach for Determining Driver Impatience and Stress Leveraging Internet of Vehicles Infrastructure," *Vehicles*, vol. 4, no. 2, pp. 553-566, 2022, doi: <https://doi.org/10.3390/vehicles4020032>.
- [8] S. Khadim, F. Riaz, S. Jabbar, S. Khalid, and M. Aloqaily, "A non-cooperative rear-end collision avoidance scheme for non-connected and heterogeneous environment," *Computer Communications*, vol. 150, pp. 828-840, 2020, doi: <https://doi.org/10.1016/j.comcom.2019.11.002>.
- [9] N. Williams and M. Barth, "A Qualitative Analysis of Vehicle Positioning Requirements for Connected Vehicle Applications," *IEEE Intelligent Transportation Systems Magazine*, vol. 13, no. 1, pp. 225-242, 2021, doi: <https://doi.org/10.1109/MITS.2019.2953521>.
- [10] S. Knowles Flanagan, Z. Tang, J. He, and I. Yusoff, "Investigating and Modeling of Cooperative Vehicle-to-Vehicle Safety Stopping Distance," *Future Internet*, vol. 13, no. 3, p. 68doi: <https://doi.org/10.3390/fi13030068>.
- [11] T. Xia and H. Chen, "A Survey of Autonomous Vehicle Behaviors: Trajectory Planning Algorithms, Sensed Collision Risks, and User Expectations," *Sensors*, vol. 24, no. 15, p. 4808doi: <https://doi.org/10.3390/s24154808>.
- [12] G. Luo et al., "An over-the-horizon potential safety threat vehicle identification method based on ETC big data," *Heliyon*, vol. 9, no. 9, 2023, doi: <https://doi.org/10.1016/j.heliyon.2023.e20050>.
- [13] Q. Wu, L. C. K. Hui, C. Y. Yeung, and T. W. Chim, "Early car collision prediction in VANET," in *2015 International Conference on Connected Vehicles and Expo (ICCVE)*, 2015, pp. 94-99, doi: <https://doi.org/10.1109/ICCVE.2015.55>.
- [14] G. Rakesh and M. Belwal, "Vehicle Collision Avoidance in a VANET environment by data communication," in *2019 3rd International Conference on Computing Methodologies and Communication (ICCMC)*, 2019, pp. 238-242, doi: <https://doi.org/10.1109/ICCMC.2019.8819797>.
- [15] H. A. H. Naji, Q. Xue, N. Lyu, X. Duan, and T. Li, "Risk Levels Classification of Near-Crashes in Naturalistic Driving Data," *Sustainability*, vol. 14, no. 10, p. 6032, 2022, doi: <https://doi.org/10.3390/su14106032>.

- [16] M. S. Sheikh and Y. Peng, "Assessment of Rear-End Collision Risk Based on a Deep Reinforcement Learning Technique: A Break Reaction Assessment Approach," *IEEE Access*, vol. 13, pp. 20171-20190, 2025, doi: <https://doi.org/10.1109/ACCESS.2025.3534787>.
- [17] J. Hang, X. Yan, X. Li, K. Duan, J. Yang, and Q. Xue, "An improved automated braking system for rear-end collisions: A study based on a driving simulator experiment," *Journal of Safety Research*, vol. 80, pp. 416-427, 2022, doi: <https://doi.org/10.1016/j.jsr.2021.12.023>.
- [18] Y. Djenouri, A. N. Belbachir, T. Michalak, A. Belhadi, and G. Srivastava, "Enhancing smart road safety with federated learning for Near Crash Detection to advance the development of the Internet of Vehicles," *Engineering Applications of Artificial Intelligence*, vol. 133, p. 108350, 2024, doi: <https://doi.org/10.1016/j.engappai.2024.108350>.
- [19] J. Yuan, M. Abdel-Aty, Y. Gong, and Q. Cai, "Real-Time Crash Risk Prediction using Long Short-Term Memory Recurrent Neural Network," *Transportation Research Record*, vol. 2673, no. 4, pp. 314-326, 2019, doi: <https://doi.org/10.1177/0361198119840611>.
- [20] L. Wang, F. Nie, J. Park, M. Abdel-Aty, and W. Ma, "Drivers' Rear-end Conflict Risk Avoidance Behaviors Prediction Based on Natural Driving Data," *IEEE Transactions on Intelligent Vehicles*, pp. 1-11, 2024, doi: <https://doi.org/10.1109/TIV.2024.3417001>.
- [21] A. Abdelraouf, M. Abdel-Aty, Z. Wang, and O. Zheng, "Trajectory prediction for vehicle conflict identification at intersections using sequence-to-sequence recurrent neural networks," *arXiv preprint*, 2022, doi: <https://doi.org/10.48550/arXiv.2210.08009>.
- [22] D. Vijayan, M. Saad, and A. M. Khedr, "Bayesian Optimized Enhanced Ensemble Multi-Layer Perceptron for Rear-End Collision Prediction in IoV," *IEEE Access*, vol. 12, pp. 193693-193706, 2024, doi: <https://doi.org/10.1109/ACCESS.2024.3519177>.
- [23] Z. Xie, Y. Ma, Z. Zhang, and S. Chen, "Real-time driving risk prediction using a self-attention-based bidirectional long short-term memory network based on multi-source data," *Accident Analysis & Prevention*, vol. 204, p. 107647, 2024, doi: <https://doi.org/10.1016/j.aap.2024.107647>.
- [24] S. S. Magdum, A. Franklin, and B. R. Tamma, "A Cooperative Federated Learning Mechanism for Collision Avoidance using Cellular and 802.11p based Radios Opportunistically," in *2021 IEEE International Conference on Advanced Networks and Telecommunications Systems (ANTS)*, 2021, pp. 284-289, doi: <https://doi.org/10.1109/ANTS52808.2021.9936930>.
- [25] S. Liu, Y. Fu, P. Zhao, F. Li, and C. Li, "Autonomous Braking Algorithm for Rear-End Collision via Communication-Efficient Federated Learning," in *2021 IEEE Global Communications Conference (GLOBECOM)*, 7-11 Dec. 2021, pp. 01-06, doi: <https://doi.org/10.1109/GLOBECOM46510.2021.9685298>.
- [26] L. Tang, M. Wen, Z. Shan, L. Li, Q. Liu, and Q. Chen, "Digital Twin-Enabled Efficient Federated Learning for Collision Warning in Intelligent Driving," *IEEE Transactions on Intelligent Transportation Systems*, vol. 25, no. 3, pp. 2573-2585, 2024, doi: <https://doi.org/10.1109/TITS.2023.3330938>.
- [27] D. Deva Hema and T. Rajeeth Jaison, "Efficient Collision Risk Prediction Model for Autonomous Vehicle Using Novel Optimized LSTM Based Deep Learning Framework," *International Journal of Intelligent Transportation Systems Research*, vol. 22, no. 2, pp. 352-362, 2024, doi: <https://doi.org/10.1007/s13177-024-00399-z>.
- [28] Q. Xue, J. Lu, and K. Gao, "Driving Style Recognition Incorporating Risk Surrogate by Support Vector Machine," Singapore, 2021: Springer Singapore, in *Smart Transportation Systems 2021*, pp. 123-131, doi: https://doi.org/10.1007/978-981-16-2324-0_13.
- [29] Q. Lim, Y. Lim, H. Muhammad, D. W. M. Tan, and U. X. Tan, "Forward collision warning system for motorcyclist using smart phone sensors based on time-to-collision and trajectory prediction," *Journal of Intelligent and Connected Vehicles*, vol. 4, no. 3, pp. 93-103, 2021, doi: <https://doi.org/10.1108/JICV-11-2020-0014>.

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- [30] X. Ma, Q. Yu, and J. Liu, "Modeling Urban Freeway Rear-End Collision Risk Using Machine Learning Algorithms," *Sustainability*, vol. 14, no. 19, p. 12047, 2022, doi: <https://doi.org/10.3390/su141912047>.
- [31] M. Song and J.-H. Wang, "Studying the tailgating issue in rhode island and its treatment," in *51st Annual Transportation Research Forum*, Arlington, Virginia, US, 11-13 March, 2010: Transportation Research Forum, pp. 1 - 18, doi: <https://doi.org/10.22004/ag.econ.207265>.