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Research paper

Enhancing smart road safety with federated learning for Near Crash Detection to advance the development of the Internet of Vehicles

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ABSTRACT

We introduce an innovative methodology for the identification of vehicular collisions within Internet of Vehicles (IoV) applications. This approach combines a knowledge base system with deep learning for model selection in an ensemble learning setting. It is designed to provide a general near-crash detection capability without relying on domain-specific knowledge, enabling the development of generic deep learning models. Our proposed methodology employs a novel deep learning approach, wherein multiple learning models are individually trained for each image. Subsequently, visual features are computed and stored for each trained image, along with the associated loss values from the training phase. This stored information is utilized to select the most suitable models for processing new image data during the testing phase. To facilitate efficient model selection, we employ a kNN (k Nearest Neighbors) strategy. To enhance both data and model security in IoV environments, we implement an intelligent federated learning (FL) strategy. Users are organized into clusters, and we employ two distinct aggregation methods, departing from conventional federated learning approaches. In the initial stage, we aggregate model data from all users to create a global model representing collective knowledge. In the subsequent stage, we aggregate models from each cluster to generate customized local models. Users are provided with both global and local models, allowing them to select the most suitable model for their specific crash detection needs. We test our approach, that we call Knowledge Guided Deep Learning for Near Crash Detection (KGDL-NCD), on well-known NCD benchmarks. The results demonstrate that KGDL-NCD surpasses baseline solutions, achieving an AUC (Area Under Curve) metric of 0.95.

1. Introduction

The Internet of Vehicles (IoV) involves integrating vehicles, communication networks, and the Internet to create intelligent transportation systems (Cheng et al., 2015). IoV allows vehicles to communicate with each other and with the surrounding infrastructure, facilitating information exchange for purposes like traffic management (Wang et al., 2018; Sun et al., 2022), driver assistance (Zhang and Letaief, 2019; Xu et al., 2022a), and safety improvements (Zhou et al., 2020; Xu et al., 2021). A typical application of IoV is e-commerce and last-mile delivery services, where IoV provides faster and more efficient delivery of goods to consumers (Wang et al., 2019). Delivery companies can optimize routes, track shipments in real-time, and provide customers with accurate delivery estimates using IoV-enabled logistic solutions. This integration contributes to the growth of the digital economy by improving supply chain efficiency and enhancing the overall shopping experience for consumers.

Federated learning (FL) is a decentralized machine learning (ML) approach in which multiple devices or entities collaboratively train a model without sharing their raw data (Sun et al., 2020; Fu et al., 2023). In the context of IoV, FL can harness the collective intelligence

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of vehicles while safeguarding data privacy (Ji et al., 2021; Pham et al., 2022). Instead of sending sensitive data to a central server, training occurs locally on the vehicles themselves. The resulting models are then combined, and the shared knowledge is used to enhance various IoV applications, including predictive maintenance, traffic prediction, and anomaly detection. By merging the capabilities of IoV and FL, we can tap into the distributed intelligence of vehicles while upholding privacy concerns. This approach paves the way for robust and privacy-preserving AI models that can improve IoV's efficiency, safety, and overall intelligence (Zhao et al., 2023).

Near Crash Detection (NCD) represents a formidable challenge within the context of the Internet of Vehicles (IoV), particularly when applied to real-world scenarios characterized by a diverse range of conditions and unforeseen events. NCD primarily aims to discern deviations from ordinary and expected vehicular behavior by analyzing car data. This typically involves constructing a model of what constitutes normal behavior, and then utilizing this model to flag instances that fall outside the scope of this learned distribution as anomalies or potential crash events. Multiple approaches exist for NCD, including:

1. Advanced Driver Assistance Systems (ADAS): ADAS technologies encompass features such as forward collision warning, automatic emergency braking, lane departure warning, and blind spot detection. These systems employ sensors and cameras to monitor a vehicle's surroundings and issue alerts or take corrective actions when they detect an impending collision (Sethuraman et al., 2023; Wu et al., 2023; Wang et al., 2023a).
2. Vehicle-to-Vehicle (V2V) Communication: V2V technology enables vehicles to communicate with one another, sharing critical information such as speed, direction, and position. This facilitates anticipatory responses to potential collisions, aiding drivers in avoiding accidents (Moradi-Pari et al., 2023; Shao et al., 2023; Xiao et al., 2022).
3. Driver Monitoring Systems (DMS): DMS relies on sensors and cameras to observe the driver's behavior and attentiveness. DMS can detect signs of drowsiness, distraction, or impairment and issue alerts to refocus or prompt a break, thereby reducing the risk of crashes attributed to human factors (Mohammed et al., 2023; Su et al., 2023; Xiao and Konak, 2016).

NCD assumes a pivotal role in the identification of potential issues or concerns, thereby facilitating data-driven decision-making within transportation organizations. For instance, a deep learning approach may involve training a convolutional neural network on an extensive dataset of transportation-related events to discern unusual patterns that might signal an impending crash event. Crafting a robust and efficient model for NCD is a formidable task because identification of anomalous patterns from images can yield ambiguous results. Defining what qualifies as anomalous in real-world video scenes, replete with diverse types, shapes, and sizes of anomalies, demands a method capable of learning features that encapsulate the predominant variability in these image patterns. In this context, various strategies have been explored to optimize the NCD learning process. These strategies delve into advanced deep learning architectures, such as adversarial neural networks and integrated convolutional neural networks (Lin et al., 2020; Huang et al., 2020; Yang et al., 2023). These innovations aim to enhance the efficacy of NCD systems and address multifaceted challenges associated with identifying near-crash events in IoV environments. Numerous challenges persist in the realm of Near Crash Detection (NCD)-based solutions, with one prominent concern revolving around variability in model performance. Specifically, distinct models exhibit varying degrees of efficacy in addressing specific categories of outliers, with some excelling in mitigating certain types of anomalies while others demonstrate superior effectiveness in dealing with different outlier patterns. An alternative approach to tackle this issue is to employ ensemble learning, as proposed by Choi et al. (2021) in the context of vehicular applications. Ensemble learning seeks to determine the most suitable model for each novel observation. However, it is noteworthy that utilization of ensemble models introduces significant computational demands, both in terms of time and memory resources, as all constituent models within the ensemble must be loaded and executed during the inference phase. Furthermore, an additional challenge arises when one or more models within the ensemble negatively impact the overall learning process. In response to the aforementioned issues, this study endeavors to address the following critical research question: Given a set of NCD-based models denoted as $\mathcal{M}$, and a collection of new video scenes denoted as $\mathcal{I}_{new}$, can we discern in advance which models in $\mathcal{M}$ positively contribute to $\mathcal{I}_{new}$ and which ones may have a negative impact? In other words, can we pre-determine models within $\mathcal{M}$ that enhance the performance for $\mathcal{I}_{new}$?

To answer the above research question, we require a method to integrate prior knowldge in the ensemble. Indeed, the integration of prior knowledge has emerged as a highly effective approach to augmenting the performance of deep learning methods. Embedding existing knowledge into deep learning models consistently results in enhanced performance, an especially valuable advantage in scenarios where labeled data is limited or when addressing intricate tasks such as Near Crash Detection (NCD). Nevertheless, undertaking such endeavors demands the expertise of data scientists, and in the context of NCD, a profound comprehension of the domain, presenting a non-trivial challenge.

In this paper, we seek to provide solutions to these challenges by introducing a novel approach that we call Knowledge Guided Deep Learning for Near Crash Detection (KGDL-NCD). KGDL-NCD strives at leveraging prior knowledge to enhance effectiveness of NCD models in dealing with novel observations and addressing the issues of model selection and ensemble performance.

The primary contributions of our research encompass a multifaceted exploration of the integration of prior knowledge into deep learning frameworks for NCD. To the best of our knowledge, this work is the first comprehensive attempt to harness insights from training data to address and enhance the efficacy of NCD methodologies. We hope that the innovative KGDL-NCD approach presented in this paper marks a significant step forward in the quest for more robust and informed solutions to NCD challenges.

In more detail, our contributions can be summarized as follows:

1. Introduction of KGDL-NCD, a novel approach designed to harness insights derived from data to determine the most appropriate model for each testing dataset, thereby advancing the overarching field of NCD.
2. Development of an intelligent inference mechanism involving the calculation of visual features for each image in the testing dataset. This information is then compared with data stored in the knowledge base created during the training phase using k-Nearest Neighbors (kNN) to select the most suitable model during the inference phase.
3. Implementation of an intelligent FL strategy aimed at enhancing data and model security in Internet of Vehicles (IoV) environments. This strategy involves clustering IoV users into distinct groups.
4. Adoption of a dual-stage aggregation approach. In the first stage, model data from all users is combined to create a global model, representing a collective understanding derived from the entire user population. In the second stage, models from each cluster are aggregated to generate local models specific to comparable users, allowing for more customized and fine-tuned models within each cluster.
5. Evaluation of the KGDL-NCD method on well-known NCD benchmarks, employing the area under the curve (AUC) metric. The results demonstrate that the proposed approach outperforms baseline solutions in terms of outcome quality and exhibits competitive performance in terms of inference runtime.

2. Related work

This paper is surrounded into two main topics: knowledge based solutions, and near crash detection solutions.

2.1. Knowledge based solutions

Hou et al. (2022) brought forth the concept of GuidedStyle as a means to perform semantic face editing with pretrained StyleGAN (Karras et al., 2020). This innovation empowers the attention mechanism inherent in the StyleGAN generator, allowing it to actively choose a specific layer for precise style adjustments. By enhancing the generator's attention mechanism, it gains the ability to pinpoint and focus on an individual layer within its architecture, resulting in a more precise influence on stylistic attributes. This advancement opens up possibilities for refining the generator's output, enabling more targeted and controlled style modifications, ultimately providing greater creative control in generative image synthesis. Dong et al. (2021) introduced an iterative approach using a deep denoiser, specialized in reducing noise while preserving essential image features. This iterative denoising process combines the inherent capabilities of the deep image prior, which captures intrinsic image characteristics, with a likelihood function derived from domain-specific insights. By iteratively applying denoising operations while considering the observation matrix, the optimization procedure becomes finely tuned to both the underlying image structure encoded by the deep image prior and the constraints provided by domain knowledge. Li et al. (2022c) presented a novel deep collaborative fusion network guided by domain knowledge within a specific domain. The network's encoder is designed to extract complementary information from multiple modalities, while the multi-branch decoder handles tasks related to semantic segmentation and multimodal reconstruction. This configuration facilitates the achievement of multi-classification goals through multitask learning. Li et al. (2022b) introduced a collaborative boosting framework that iteratively merges two distinct components: a knowledge-guided ontology reasoning module and a data-driven deep learning module. The ontology reasoning module integrates intra-taxonomy reasoning, a crucial element that improves classification performance. Li et al. (2022a) devised a knowledge encoder–decoder framework guided by an auxiliary signal. External linguistic cues are incorporated to enhance the decoder's incorporation of existing knowledge in the pre-training phase. Furthermore, the method includes exploring auxiliary patches to enhance the collection of visual patch characteristics before introducing them to the transformer encoder. Yang et al. (2022) presented a novel attention mechanism guided by semantics, leveraging semantic knowledge to direct visual perception. The innovative class embedding showcases enhanced discriminative ability, particularly in scenarios with constrained sample sizes. The procedure involves training a feature extractor to transmit visual prior knowledge from well-established base classes to a specific set of images that accurately represent each new class. Subsequently, this information is amalgamated to form a cohesive visual prototype. Xu et al. (2022b) explored both knowledge-driven and data-driven approaches to evaluate the effectiveness of the traffic prediction methods. It revealed the inherent difficulty in significantly enhancing accuracy. Consequently, the authors introduced a novel trajectory prediction framework tailored for diverse traffic agents. In this framework, residual knowledge supplements data-driven techniques, rectifying outcomes to align more closely with real-world traffic dynamics while maintaining high precision.

2.2. Near crash detection solutions

Several works have been developed for near-crash detection. Sattar et al. (2023) aimed to replicate car crash injuries through the application of three advanced ML algorithms: TabNet, MLP with embedding layers, and a standard multi-layer perceptron (MLP) implemented in Keras. Among these models, TabNet stands out as a complex framework designed for tabular data, incorporating attention-based networks. Hyperparameter tuning was performed using Bayesian optimization to improve the predictive performance of these models. Almutairi et al. (2023) proposed a hybrid approach that combines Deep Recurrent Neural Networks (DRNN) and Long Short-Term Memory (LSTM) techniques, denoted as DRNN-LSTM. The authors created a dataset by simulating an Internet of Vehicles (IoV) scenario and employed DRNN-LSTM to detect rear-end collisions within this context. Sultani et al. (2018) recommended the use of training frames with limited labeling, where training labels were assigned at the video level rather than the clip level. They applied deep multiple instance ranking architecture for anomaly detection, employing multiple instance learning (MIL) to develop a deep anomaly ranking model that assigns high anomaly scores to abnormal video segments. Sparsity and temporal smoothness constraints were introduced in the ranking loss function to improve anomaly localization during training. Haresh et al. (2020) proposed a data-driven anomaly detection concept using dashcam videos. The authors utilized reconstruction-based loss and one-class classification loss to identify anomalies in static camera and retro truck data. Additionally, the authors introduced priors for models representing object interactions in this context. Thakare et al. (2022) introduced a novel technique that leverages object information and their spatial locations. This approach involved high-level post-processing to elucidate the severity and context of accidents while also localizing accident occurrences in video frames. The process segmented input videos into pre-accident, accident, and post-accident stages and applied a refinement process to filter interaction proposals. An iterative training process was used to classify regular interactions and accidents, with heat maps highlighting damaged areas. Finally, high-level textual descriptions were generated to assess the accident's context and seriousness.

2.3. Discussions

Current guided deep learning methods face a primary challenge rooted in their inherent specificity, tailoring each model to a particular application. This specialization often leads to a disregard for overall data distribution, particularly when identifying abnormal images. Moreover, issues related to model security and data privacy are evident, with insufficient protection of model information within IoV platform components. A thorough examination of existing literature highlights the need to overcome these challenges, emphasizing the necessity for a high level of expertise from data scientists, especially within NCD. This requires professionals with profound knowledge of the specific application domain, making the task demanding. In response to these challenges, our study takes a different approach by independently training a model without relying on guidance from domain experts. We adopt a comprehensive NCD deep learning strategy that capitalizes on the inherent information within training data. Additionally, we explore the realm of FL to address privacy and data ownership concerns. This involves training models within IoV environments, providing a solution to safeguarding sensitive information and ensuring a more secure and privacy-conscious deep learning approach.

3. Method design

3.1. Principle

The KGDL-NCD methodology is illustrated in Figs. 1, and 2. It integrates concepts from deep learning, k-nearest neighbors (kNN), and relevant knowledge derived from both training and testing datasets. The fundamental idea involves training multiple deep learning models during the training phase, and this acquired knowledge is subsequently utilized to determine the optimal model for deployment during the inference phase for each unique testing image. The process begins with

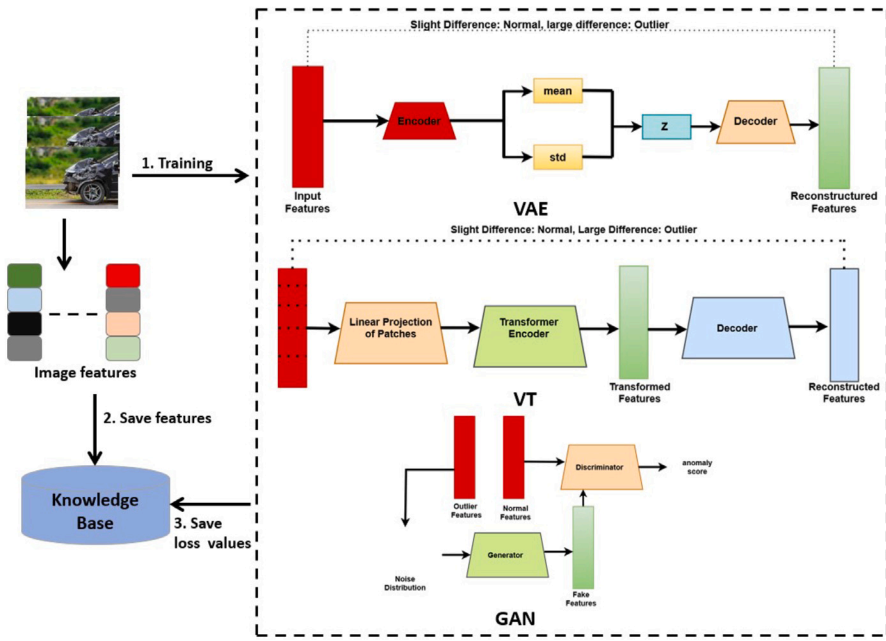

Fig. 1. Training of KGDL-NCD: To begin, the process initiates with the extraction of training data, followed by the training of deep learning models. These models' training information is then carefully preserved within a knowledge base, facilitating the meticulous aggregation of outcomes.

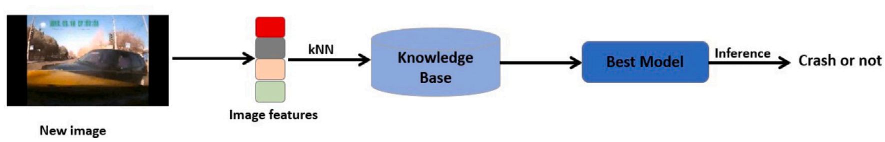

Fig. 2. Inference of KGDL-NCD: The aptness of a model for a specific test dataset is assessed through the application of the k-Nearest Neighbors (kNN) technique.

data extraction from a diverse set of images. Following this, a variety of deep learning architectures are trained, with valuable insights gained from this training process consolidated in a knowledge repository. This knowledge, along with the k-nearest neighbors approach, is then used to identify the most suitable model for a given test dataset during the inference phase. The selection of similar images is accomplished through the application of the k-nearest neighbors technique. For a more comprehensive understanding of the components comprising the KGDL-NCD methodology, a detailed explanation is provided in the subsequent discussion.

3.2. Training

Consider a collection of l images/frames used in the training process, denoted as $I = \{I_1, I_2, \dots, I_l\}$. The training is conducted using a set of n models, denoted as $\mathcal{M} = \{\mathcal{M}_1, \mathcal{M}_2, \dots, \mathcal{M}_n\}$. Each image I_i is fed into each model $\mathcal{M}_j$ for training. Subsequently, the loss value v_{ij} is computed for each model $\mathcal{M}_j$. In our specific setting, three models are used: Variable AutoEncoder (VAE) (Eduardo et al., 2020), Visual Transformer (VT) (Cultrera et al., 2023), and Generative Adversarial Network (GAN) (Liu et al., 2019). These models are well-known deep learning models for outlier detection, and they proved their efficiency in a wide range of applications. The features of I_i (represented as F_i) and the loss value v_{ij} are stored in the knowledge base. Standard back-propagation is used to adjust the weights of the models in $\mathcal{M}$. For hyperparameter optimization of the n models, the Greedy Hyperparameter Optimization (GHO) algorithm (Rajendran et al., 2021) is employed. GHO follows a strategic approach to achieve convergence towards a localized optimal solution while minimizing the computational burden associated with exhaustive hyperparameter optimization. It iteratively optimizes each hyperparameter while keeping other parameters fixed, progressing until all hyperparameters have been systematically fine-tuned. By addressing each hyperparameter individually within this iterative framework, the GHO algorithm navigates the complex parameter space towards an optimal configuration. After this step, the following variables are created and saved:

1. n matrices, each denoted as matrix $W^{(i)}$, which represents the trained weights of model $\mathcal{M}_i$.
2. The knowledge base KB, consisting of l rows. The i^{th} row contains relevant information about image I_i, including its features F_i and the set of n loss values $\{v_{i1}, v_{i2}, \dots, v_{in}\}$.

3.3. Inference

In the inference stage, our process unfolds as follows: we begin by extracting features, denoted as F_{new}, from the new image, represented as I_{new}. Our subsequent step involves tapping into the knowledge base, denoted as KB, to select the most suitable model for inference. This model selection process is facilitated by the k-Nearest Neighbors (kNN) algorithm (Svahn and Sysoev, 2022). kNN is the well-known machine learning algorithm widely used for search selection in different knowledge based systems. The kNN algorithm calculates distances between the features of the new image and those of all training images within the knowledge base, thereby identifying images with the closest resemblance to the new image. The size of the neighborhood, a user-specified integer k, defines this neighborhood within the space of computed distances. The selected best model is then utilized for inference, determining the output for the new image by either aggregating majority votes or calculating an average estimate from the k nearest neighbors, which are the k closest images in terms of distance. However, to tackle the challenge of varying image data distributions caused by data drift, we propose a modified version of kNN that adjusts distances to account for image feature variations. This adaptation is necessary because traditional Euclidean distance measures can yield inaccuracies when applied to image data, primarily due to the diverse distribution patterns arising from data drift. To accurately assess image similarities, we recommend employing an end-to-end similarity metric learning network. This process involves computing feature dissimilarities between attributes of the new image and those of all training images within the knowledge repository, revealing images that bear the highest resemblance to the new input. The user-defined integer k dictates the extent of the local neighborhood to consider, defined within the domain of computed distance metrics, encapsulating relational distances among images. The crucial step of selecting the optimal model for inference is then executed, which involves aggregating preferences or averaging predictions from the k nearest neighbors within the designated neighborhood. The decision-making process leverages contributions from the k closest images, as determined by their distance measures. To further enhance the robustness of this methodology, we propose a modified variant of the k-nearest neighbors (kNN) approach. This adaptation includes computing distances that have been adjusted to accommodate the intricate nuances of image features. Traditional distance metrics, such as the Euclidean distance, often prove ill-suited for image data due to intricate and varied distribution patterns stemming from data drift issues. This variance complicates the accurate measurement of image similarities. Rather than relying directly on manually curated similarity metrics to address this challenge, we advocate for the integration of an end-to-end similarity metric learning network. This network, tailored to the unique characteristics of image data, offers a more effective solution for capturing nuanced image relationships within a dynamically evolving data landscape. The proposed similarity metric is made up of two key components:

1. **Similarity Metric Network**: This is a fully connected neural network designed to assess the similarity between the visual features of two images. To measure the degree of similarity between features of the newly encountered image and those of the trained images, we employ a fully connected neural network featuring a single hidden layer. The inputs for the similarity assessment function consist of the feature vector of the new image, denoted as F_{new}, and the feature vector of each trained image, represented as F_{I_i}:

$$S(F_{new}, F_{I_i}) = 1 - \sigma\left(\text{concat}([F_{new}, F_{I_i}]) \times C\right) \tag{1}$$

   Here, C represents the coefficient of the similarity metric function.
2. **Smooth Similarity Loss Learning**: The optimization of the similarity metric function, through backpropagation, involves evaluating the surrogate loss of the similarity network established in the initial step. During network training, we generate synthetic images from various distributions. To establish the ground truth, i.e., the true similarity value, we assess the similarity between distributions of the available images.

In the end, we leverage the weight parameters of the most optimal model to derive inferences for the new image, enabling a more sophisticated and precise decision-making process.

3.4. Federated learning deployment

Within the Internet of Vehicles (IoV) context, where numerous users are integral to the system, we employ a FL framework to enable collaborative model training. This framework facilitates the collective training of ML models by leveraging data sourced from vehicles in a decentralized manner. In this scenario, vehicles contribute substantial volumes of data, forming the foundation for model improvement through FL. The adoption of FL presents several advantages, including safeguarding user privacy, reducing communication overhead, and enhancing model customization on a per-vehicle basis. Our proposed solution seeks to address ongoing concerns surrounding the federated training process. By incorporating FL principles into IoV environments, we aim to address and alleviate these concerns, fostering a secure and efficient collaborative model refinement environment. Our approach tackles three key aspects:

a. **User Clustering**: In the IoV ecosystem, denoted as $U = \{u_1, u_2, \dots, u_N\}$, where N represents the total number of users, we initiate user clustering. This process involves grouping similar users based on specific criteria. Let $C = \{C_1, C_2, \dots, C_K\}$ represent the clusters, where K indicates the total number of clusters. To mathematically define user clustering, we introduce binary variables x_{ij} for each user u_i and each cluster C_j, as follows:

$$x_{ij} = \begin{cases} 1 & \text{if user } u_i \text{ belongs to cluster } C_j \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

To ensure that each user belongs to only one cluster, the following constraint is imposed:

$$\sum_{j=1}^{K} x_{ij} = 1, \forall u_i \in U$$

A similarity measure between users, denoted as $d(u_i, u_j)$, guides the clustering process. The objective of user clustering is to maximize the overall similarity within each cluster while minimizing the similarity between different clusters. This is expressed through the following objective function:

$$\text{Maximize } \sum_{i=1}^{N}\sum_{j=1}^{N} d(u_i, u_j) \sum_{k=1}^{K} x_{ik}x_{jk}$$

Solving this optimization problem yields the optimal clustering solution, where each user is assigned to a specific cluster based on calculated similarities. The clustering algorithm iteratively assigns users to the cluster that maximizes the similarity score, and the process continues until convergence. Note that this algorithm assumes a fixed number of clusters, and the choice of similarity measures depends on the specific characteristics of the IoV system.

b. **Transmitting the Trained Local Models**: System initialization includes setting up public parameters, generating keys, and distributing data among various roles within the system. A trusted authority generates codes for transferring and validating model data. The server receives local models trained by users in each cluster, along with their architecture, weights, and respective user IDs. Before transmission, these models are encrypted using homomorphic encryption techniques.

c. **Checking Model Integrity**: The trusted authority rigorously verifies the authenticity of each local model uploaded to the server. This verification process involves maintaining, signing, and issuing digital certificates for each model. Additionally, the accuracy of each model is thoroughly assessed to ensure its reliability.

d. **Model Aggregation**: Two forms of aggregation are utilized. The first involves aggregating the local models within each user cluster, represented as $W^{(local)_{C_j}}$. The second step combines all models to identify the global model $W^{(global)}$. The formulas are as follows:

$$W^{(local)_{C_j}} = \sum_{u_i^{C_j}} \frac{|d_i|}{|\sum_{d_i}^{D^{C_j}}|} W_i^{(local)} \tag{3}$$

and

$$W^{(global)} = \sum_{u_i}^{\mathcal{U}} \frac{|d_i|}{|\sum_{d_i}^{D}|} W_i^{(local)} \tag{4}$$

Here, C_j represents the jth cluster of users, $\mathcal{U} = \{u_1, u_2, \dots, u_k\}$ is the set of k users, and $D = \{d_1, d_2, \dots, d_k\}$ is the set of k datasets, each containing trained data for one user in $\mathcal{U}$. $W_i^{(local)}$ denotes the weights of the local model for user u_i.

e. **Sharing Updated Global Model**: After the server aggregates the results, all users receive aggregated outcomes. For near-crash detection, users utilize the aggregated local model specific to their cluster if they are influenced by other similar users. Otherwise, they employ the aggregated global model.

It is crucial to emphasize that verification mechanisms are integral to both the uploading and aggregation processes. One-way hash techniques are employed for backup and recovery verification, ensuring data integrity and security. Additionally, a stratified random sampling methodology is utilized to generate a new random number for each iteration, bolstering the system's robustness. To further refine and enhance the model, the second and third steps are repeated. Each user resets the locally encrypted global model upon receiving the updated weight parameters. This iterative process continues to iteratively improve the model over time.

4. Performance evaluation

A rigorous set of experiments has been conducted to thoroughly assess the performance of the KGDL-NCD solution. In this evaluation, we compare the KGDL-NCD's performance against a selection of state-of-the-art NCD-based methods, including MLP (Sattar et al., 2023), DRNN-LSTM (Almutairi et al., 2023), ViT-SSA (Abdelraouf et al., 2022), TransCAR (Pang et al., 2023), and CGAN (Zarei et al., 2023).

4.1. Datasets and evaluation metrics

We evaluate the designed system using the following datasets:

1. **Car Crash Dataset (CCD)**: This dataset[1] is curated for the analysis of traffic accidents. It encompasses authentic traffic accident recordings captured by dashcams mounted on moving vehicles, which hold significant value for the development of safe self-driving technology. The dataset includes a variety of accident annotations, such as weather conditions (day/night, snowy/rainy/good), and whether ego-vehicles were involved.
2. **CrashedCars (cC)**: This dataset is explicitly assembled to scrutinize traffic accidents. It is made up of genuine recordings of traffic incidents sourced from dashcams affixed to vehicles in motion, a critical component for the development of secure self-driving technology. The dataset consists of 2004 images, with 1273 images depicting scenes after crashes and 731 images depicting scenes before crashes. Each image boasts dimensions of 720 × 1280 pixels and comprises 3 RGB channels.
3. **BDD**: This dataset, as cited in Bao et al. (2020), is a collection of traffic accident videos procured by extracting content from YouTube channels. The videos were subsequently segmented to generate a total of 1500 trimmed video clips. Each video clip is composed of 50 frames, with a temporal resolution of 10 frames per second. Additionally, a separate set of 3000 non-accident videos was randomly selected from the BDD100K dataset to diversify the dataset's content.

For the establishment of training/testing splits, we adhere to the settings delineated in Wu et al. (2021). To evaluate the performance of the KGDL-NCD solution, we employ the following well-established metrics, which are particularly pertinent to near crash detection (Akcay et al., 2019):

[1] https://github.com/Cogito2012/CarCrashDataset

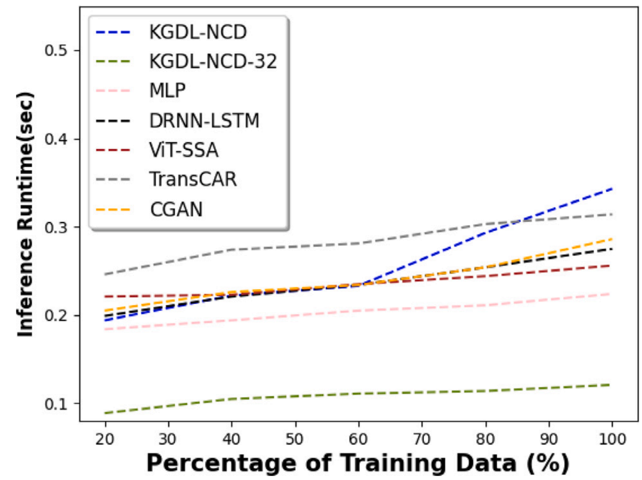

Fig. 3. KGDL-NCD Vs. SOTA solutions: Inference runtime using CCD.

Table 1
AUC performance of KGDL-NCD and state-of-the-art solutions using CCD.

Condition	KGDL-NCD	MLP	DRNN-LSTM	ViT-SSA	TransCAR	CGAN
Day	0.98	0.95	0.97	0.96	**0.99**	0.98
Night	**0.95**	0.89	0.87	0.88	0.88	0.87
Rain	**0.94**	0.91	0.92	0.93	0.92	0.91
Snow	**0.95**	0.88	0.89	0.90	0.90	0.91
average	**0.95**	0.91	0.91	0.92	0.92	0.92

1. **Area Under Curve (AUC)**: This metric quantifies the area under the receiver operating characteristic curve. The curve is a plot of the true positive rate against the false positive rate at various outlier detection thresholds. AUC values range from 0.0 to 1.0, where a score of 0.0 indicates that the model fails to detect any correct outliers, while a score of 1.0 signifies that the model adeptly detects all outliers.
2. **True Positive Rate (TPR)**: TPR is a statistical metric that gauges the accuracy of a model by quantifying the proportion of actual positive instances correctly identified by the model as positive. It essentially measures the model's ability to accurately identify instances belonging to the positive class, offering insights into its discriminatory power and precision in distinguishing between the two classes. It can be expressed by:
$$TPR = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{5}$$
3. **False Positive Rate (FPR)**: FPR is a statistical measure that assesses the precision of a model by determining the ratio of actual negative instances inaccurately classified as positive by the model. This metric sheds light on the model's tendency to produce erroneous positive predictions, offering insights into its susceptibility to incorrectly categorize instances into the positive class and providing a glimpse into its specificity and selectivity performance. It can be expressed by:
$$FPR = \frac{\text{False Positives}}{\text{False Positives} + \text{True Negatives}} \tag{6}$$

4.2. Results

The initial comparative results of visual anomaly detection using KGDL-NCD and the baseline solutions on the CCD dataset are presented in Table 1. Notably, our solution demonstrates a significant performance advantage over other state-of-the-art models in three out

Fig. 4. Qualitative Results: KGDL-NCD correctly detected these two scenarios as possible crashes, where there is a failure for the remaining solutions using CCD.

Table 2
Accuracy performances of KGDL-NCD and state-of-the-art solutions using different datasets.

Metrics	Datasets	KGDL-NCD	MLP	DRNN-LSTM	ViT-SSA	TransCAR	CGAN
TPR	CCD	0.94	0.92	0.90	0.90	0.90	0,90
	cC	0.93	0.92	0.88	0.87	0.89	0.90
	BDD	0.91	0.90	0.90	0.89	0.88	0.87
FPR	CCD	0.08	0.08	0.08	0.09	0.09	0.10
	cC	0.08	0.08	0.11	0.11	0.10	0.09
	BBD	0.09	0.10	0.09	0.11	0.11	0.12

of four cases, as illustrated in the table. The mean AUC, as depicted in the table, attains a commendable new score of 0.95, signifying an improvement of approximately 3%. This remarkable result is attributed to the utilization of a knowledge base that guides the three models employed in the scenario, facilitating their convergence towards the global optimum. Consequently, the choice of the model for inference is contingent on the similarity of the training data. Table 2 showcases the accuracy metrics of KGDL-NCD using different datasets. The presentation of accuracy metrics for KGDL-NCD involves a meticulous examination across a diverse range of datasets. This thorough analysis serves to illuminate the distinct superiority of our proposed model when compared to baseline solutions. The evaluation encompasses a comprehensive set of metrics, notably including True Positive Rate (TPR), False Positive Rate (FPR), and F-score, providing a nuanced understanding of performance. The detailed scrutiny of these metrics consistently reveals that KGDL-NCD outperforms the baseline models with a notable margin. The clarity in superiority is evident not only in isolated instances but across a spectrum of evaluation criteria, reinforcing the robustness of our model's performance. The inclusion of multiple metrics ensures a holistic assessment, substantiating our assertions regarding KGDL-NCD's heightened efficacy and superior capabilities when confronted with diverse datasets. This in-depth analysis contributes to a more nuanced and comprehensive understanding of the model's proficiency and further solidifies the claim of enhanced performance in comparison to baseline solutions.

Statistical analysis is also performed using Friedman test. To compute the Friedman test for the provided data in Table 2, we first need to rank the algorithms for each dataset based on their performance metrics. Then, we calculate the average ranks for each algorithm across all datasets and use these to compute the Friedman statistic. The average ranks for each algorithm is as follows:

$$\text{KGDL-NCD}: \frac{1+1+1+4.5+4+5}{6} = 3$$

$$\text{MLP}: \frac{2+2+2+4.5+4.5+5}{6} = 3.5$$

$$\text{DRNN-LSTM}: \frac{3+5+2+4.5+4.5+2.5}{6} = 3.5$$

$$\text{ViT-SSA}: \frac{4+6+4.5+2.5+2+2.5}{6} = 3.833$$

$$\text{TransCAR}: \frac{4+3+4.5+2.5+2.5+2.5}{6} = 3.333$$

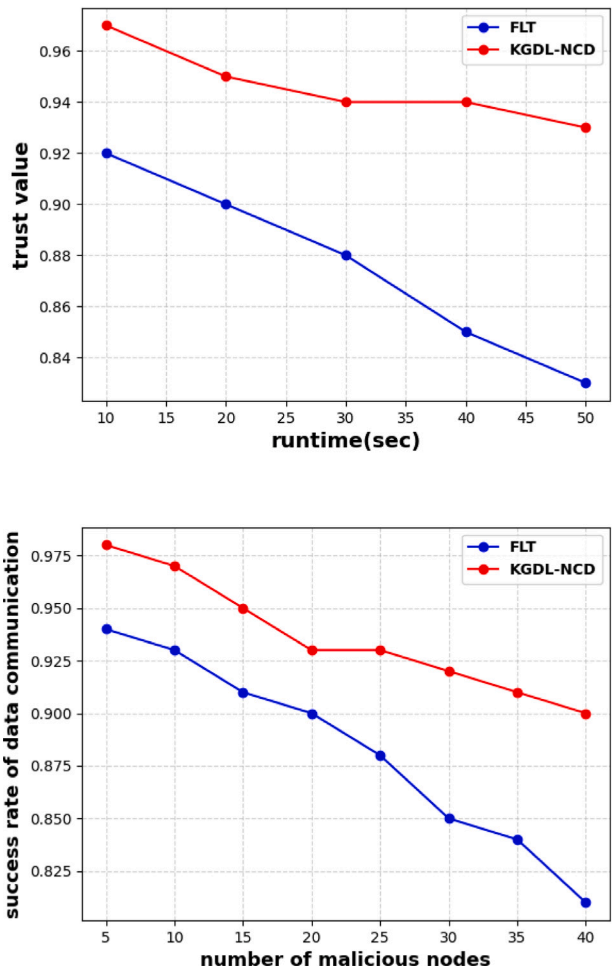

Fig. 5. Evaluation of the suggested federated learning solution and FLT framework for trustworthiness using CCD.

$$\text{CGAN}: \frac{4+3+6+6+6+1}{6} = 4.33$$

Now, we can calculate the Friedman statistic:

$$\begin{aligned}
&\text{Friedman statistic} \\
&= \frac{12}{6\times 7}\left((3^2+3.5^2+3.5^2+3.833^2+3.333^2+4.33^2)\right) - 3\times 6\times(7+1) \\
&= \frac{12}{42}(9+12.25+12.25+14.7225+11.110889+18.7689) - 144 \\
&= \frac{12}{42}\times 78.178389 - 144 \\
&\approx 22.34 - 144 \\
&\approx -121.66
\end{aligned}$$

The Friedman statistic is approximately −121.66. Now, we compare this value with the critical value from the chi-square distribution table for a chosen significance level (e.g., $\alpha = 0.05$) and the degrees of freedom ($df = 6-1 = 5$) to determine if there is a significant difference among the algorithms. For $df = 5$ and $\alpha = 0.05$, the critical value from the chi-square distribution table is approximately 15.09. Since our computed Friedman statistic (−121.66) is much lower than the critical value, we reject the null hypothesis. Therefore, there is a significant difference in the performance of the algorithms across the datasets, where the KGDL-NCD is the best one according to the average rank. To further emphasize KGDL-NCD's proficiency in crash detection, a qualitative analysis is presented in Fig. 4. The visual depiction presented here serves as a vivid testament to the KGDL-NCD approach's adeptness in successfully detecting crash incidents. This portrayal not only accentuates its proficiency but also emphasizes its unique ability to discriminate and capture critical events with a high degree of effectiveness. In stark contrast, alternative methodologies showcased in this context exhibit notable shortcomings, consistently falling short in their capacity to reliably identify and recognize crash incidents. The visual comparison vividly illustrates instances where competing methods encounter challenges, highlighting their limitations in accurately discerning crash events. In contrast, KGDL-NCD consistently demonstrates its superior performance, effectively distinguishing and capturing crucial crash incidents. This compelling visual evidence positions KGDL-NCD as an advanced and reliable solution within the domain of crash detection. The implications of these findings extend beyond mere performance metrics, indicating KGDL-NCD's potential to significantly enhance safety and reliability in applications relevant to crash detection. The visual representation not only conveys the model's efficacy but also underscores its potential practical impact, making it a compelling choice for those seeking advanced solutions in the realm of safety and reliability. The detailed evaluation of the runtime performance of KGDL-NCD in comparison to seven baseline solutions is conducted by systematically varying the percentage of training data from 20% to 100% (as shown in Fig. 3). It is noteworthy that the runtime stability of the baseline solutions remains consistently stable across the entire range of training data percentages. However, in stark contrast, KGDL-NCD's inference runtime demonstrates variability, contingent upon the specific training data utilized in the experiments. This variability is primarily attributed to the size of the knowledge base, which is actively utilized during the inference phase and is directly correlated with the size of the training data. As a consequence, KGDL-NCD exhibits competitive performance relative to the other solutions, maintaining its efficiency up to a training data percentage of 80%. However, beyond this critical threshold, the computational performance of KGDL-NCD begins to exhibit degradation. This degradation in performance beyond the 80% threshold can be attributed to the increasing complexity and computational overhead associated with the larger knowledge base utilized during inference, which ultimately impacts the runtime efficiency of KGDL-NCD. To address this issue, an optimized version of KGDL-NCD denoted as KGDL-NCD-32, has been developed. This optimized variant employs a grouping approach, wherein observations in the knowledge base are grouped into sets of 32 samples. The average values of these sample groups are considered for both the features and the loss values. The results indicate the superiority of KGDL-NCD-32 when compared to the other solutions, irrespective of the percentage of training data utilized in the experiments. This optimization effectively addresses the runtime performance concerns, ensuring consistent and improved results across a range of scenarios. The last experiment delves into a comprehensive examination of the stability metrics, leveraging the information transmission success rate and trust value to meticulously assess the efficacy of the federated learning approach that has been incorporated in this research. Each user is endowed with a trustworthiness value, spanning a range from 0 to 1, intended to gauge their reliability and the potential of their contributions. Users who exhibit a high level of trust receive scores that gravitate towards 1, signifying their credibility and dependable involvement in the collaborative process, while users with lower trust ratings tend to be closer to the 0 mark, implying a degree of skepticism regarding their contributions. To gauge the resilience and effectiveness of the federated learning system introduced in this research, it is pitted against FLT (Wang et al., 2023b), an alternative approach designed to withstand threats associated with data manipulation and replay. This comparative analysis is instrumental in evaluating the system's capacity to combat adversarial elements that may attempt to compromise the integrity of the learning process. Fig. 5 delineates disruptive activities primarily instigated by hostile users, with a predilection for executing flooding attacks. These attacks involve overwhelming the system with an abundance of often spurious data or requests, thereby presenting a substantial challenge to the system's stability and reliability. The proposed hierarchical confidence model, a pivotal component of the federated learning approach in this research, strategically utilizes a trusted authority and analytical insights to comprehensively evaluate the overall stability of node trust values. The foundation of this model lies in the fundamental principle that, even in the presence of attackers, the structured trust framework ensures the continued provision of accurate and dependable information to authentic and reliable models within the user group. The manifestation of flooding attacks, for instance, may induce heightened energy consumption among users. By meticulously monitoring energy usage patterns at the network edges, the prompt identification of malevolent users becomes feasible, enabling the implementation of appropriate measures to mitigate their disruptive actions. This hierarchical confidence model, integrated with the federated learning approach, serves as a robust defense mechanism against potential threats. It reinforces the system's stability and resilience in the face of adversarial elements, enhancing its ability to withstand and counter disruptive activities initiated by hostile users. '

4.3. Future directions

Even though the designed solution gives promising results for detecting near crash in IoV environments, several future directions might be conducted:

1. **Improved Sensor Fusion**: Integrating information from multiple sensors is crucial for an accurate intelligent transportation system (Sun et al., 2023). Future research could focus on enhancing sensor fusion techniques, combining data from cameras, LiDAR, radar, and other sensors. KGDL-NCD can leverage the complementary strengths of different sensors can improve the robustness and reliability of near crash detection systems.
2. **Real-time Decision Making with Reinforcement Learning**: Implementing reinforcement learning (RL) based on cooperative games techniques (Ma and Hu, 2022; Yue et al., 2023) for real-time decision-making in near crash scenarios is an area of potential advancement. RL models can learn optimal actions by interacting with the environment, allowing for adaptive responses to dynamic driving situations. Training RL models to make split-second decisions in near crash scenarios may lead to more proactive and context-aware collision avoidance systems.
3. **Explainable AI for Trust and Safety**: As KGDL-NCD becomes more complex, there is an increasing need for transparency and interpretability, especially in safety-critical applications like near crash detection. Future research may focus on developing explainable AI techniques (Djenouri et al., 2023a,b) that provide insights into the decision-making process of KGDL-NCD. This could enhance user trust and facilitate better integration of these systems into vehicles.

5. Conclusion

In this study, we introduced an innovative deep-learning methodology tailored to meet the specific requirements of NCD applications. The initial phase involves the training of numerous deep-learning models for individual sets of images. Through efficient training, visual features are computed for each image, and this information is stored. Additionally, the corresponding loss values arising from the training process are recorded and archived, forming a valuable repository of knowledge. During the subsequent testing phase, the critical task is the selection of the most suitable models for each new set of image data. We facilitate this selection process by the application of the kNN technique, ensuring optimal model choices for comprehensive testing purposes. To ensure the security of both data and trained models within IoV environments, we deploy an intelligent federated learning strategy. Initially, users are grouped into distinct clusters. Departing from conventional federated learning systems, we embrace an alternative approach, where we utilize two distinctive methods of aggregation. In the first stage, we amalgamate model data from all users to generate the global model. In the second stage, we aggregate models from each group to create local models tailored to users within the same group. Each user is then provided with both global and local models, autonomously determining which model to employ for NCD. To assess the effectiveness of our knowledge-guided deep learning system, we employ well-known NCD benchmarks. Results obtained affirm that our system not only achieves higher accuracy but also demonstrates substantial advantages in terms of inference runtime when compared with baseline methods. The principal advantage of our methodology lies in its capacity to dynamically select optimal models within the ensemble in real-time, contingent upon the characteristics of the data employed during deployment. However, its central challenge revolves around integrating human expertise and knowledge into NCD tasks. Previous research highlights that studies focusing on the fusion of human experience have primarily concentrated on natural language processing (Khalil and Pipa, 2022), indicating a notable research gap. To address this issue, our future work will involve incorporating inverse reinforcement learning (Arora and Doshi, 2021; Ma et al., 2023) into NCD, offering a promising avenue for further advancement in this field.

CRediT authorship contribution statement

Youcef Djenouri: Writing – review & editing, Writing – original draft, Formal analysis, Data curation, Conceptualization. **Ahmed Nabil Belbachir:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Tomasz Michalak:** Writing – original draft, Methodology, Data curation, Conceptualization. **Asma Belhadi:** Writing – review & editing, Methodology, Conceptualization. **Gautam Srivastava:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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