# Human-Centered Traffic Management Supporting Smart Cities and the Metaverse

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***Abstract*—In recent years, urban centers have increasingly been equipped with sensing, storage, and computational capabilities in the form of road infrastructure and intelligent vehicles, making cities smarter. These advancements make it possible for traffic management systems to provide enhanced traffic solutions to people, thus, improving the quality of their daily life. In this paper, we focus on an AI-based, human-centered traffic management system in a smart city context, which represents a core Metaverse application. The system considers both drivers' and traffic flow requirements in order to route vehicles safely and effectively. Our personalized route planner takes into account all relevant factors, such as the use of virtual edge servers to obtain real-time traffic data and vehicle sensing capabilities to estimate human behavior and state of alertness to achieve personalized and context-aware vehicle routing. The proposed system also aims to satisfy the demand for virtual edge computing resources in the context of smart cities and the Metaverse by re-routing vehicles based on computing resource availability at the micro clouds. One of the main challenges of the proposed system is ensuring its adoption rate in the user's daily life. We therefore argue that, to increase the penetration rate of the proposed solution, it is essential to inform the user about the reasoning behind the decisions made by the AI-based route planning system with explainable AI strategies and emphasize how adopting such a system can improve their quality of life.**

***Index Terms*—Metaverse, ITS, Vehicle route planner, Connected vehicles, Micro clouds, Explainable AI**

## 1. Introduction

Intelligent transportation systems (ITS) play a vital role in the creation of smart cities that enhance and simplify the lives of their inhabitants. To make cities smarter and safer, ITS encompasses a wide range of services related to advanced vehicle control systems (AVCS), advanced traveler information systems (ATIS), and advanced traffic management systems (ATMS) [1]. The incorporation of sensing, storage, and processing capabilities into vehicles and road infrastructures facilitates the provision of such services pertinent to the ITS context. In addition, the inception of connected vehicles with the ability to exchange data with their surroundings provides an added benefit to smart cities. With these advancements, Dressler et al. [2] proposed a virtual edge architecture, named V-Edge, that provides a means to share the resources of the connected vehicles available in a specific geographic area to host various applications. The data generated within the V-Edge ecosystem have the potential to digitally represent the physical world as digital twins, which have emerged as an essential building block for Metaverse applications [3].

Automotive and transportation are the primary beneficiaries of digital twin applications as they enable vehicles to make context-aware decisions by overlaying their sensor data on a virtual map. Vehicle route planning is one such application that can assist people in reaching their destinations in a safe and timely manner. Modern-day routing service providers offer several routes to reach a destination, each of which is optimized for multiple factors, such as travel time, distance, and predicted traffic conditions. However, Ceikute and Jensen [4] highlight that the time predicted by the service providers to reach the destination significantly varies from the actual time taken as the traffic scenarios around the driver varies extensively. In addition, service providers do not consider the preferences of individuals, or people have limited ways to express their preferences in the process of route selection, such as by avoiding tolls.

As a consequence, vehicle route planning is still a topic of primary importance, and numerous approaches have been developed to provide an optimal route for vehicles. In particular, Souza et al. [5], Dai et al. [6], and Abdelrahman et al. [7] offer personalized route planning by factoring in the human as one of the route-planning factors. Dai et al. [6] utilize the driver's historical trajectory data to comprehend the driver's preferences on travel costs regarding travel time, distance, and fuel consumption. However, Dai et al. [6] do not take into account real-time traffic data when planning routes that are crucial for reaching the destination within the estimated travel time. The study in Abdelrahman et al. [7] propose a route planner that accounts for road quality and the driver's risk profile along a given route. It uses crowd-sourced data to determine road quality and historical driver behavior on road segments to determine risk factors. Nevertheless, the proposed method relies on the routes provided by the service providers such as Google Maps to suggest the routes, thereby inheriting the problems of the standard service providers. In terms of safety-based route planning, Souza et al. [5] propose a comprehensive routing method that considers criminal activity along the routes to provide the user with a safe route. However, it estimates traffic conditions based on sporadic reports from the vehicles, thereby ignoring unanticipated traffic situations on the road network.

In our study, we propose a robust *AI-based, human-centered traffic management system* that factors in real-time traffic information received from virtual edge servers and an estimate of the driver's behavior, preferences, and level of attentiveness, in order to route vehicles safely and effectively. The proposed system is also designed to be robust to data dynamics, especially in the case where, due to environmental conditions, real-time data from traffic and vehicle sensors may not be available or be heavily affected by noise.

The remainder of the paper is organized as follows. Section 2 discusses the problem statement and motivation behind the proposed approach. Section 3 illustrates the proposed methodology in detail. Finally, Section 4 presents the future research directions of the work.

## 2. Problem Definition and Motivation

Vehicle route planning is a multi-objective problem that includes balancing a variety of factors in order to find the optimal route. In addition, route planning algorithms must be able to handle dynamic data, as road conditions vary over time. In general, they recommend a user the path that requires the shortest amount of time and/or distance to reach the destination. Clearly, the shortest route may not necessarily be the fastest route to the destination, as the travel time depends upon the anticipated traffic conditions along the routes. Google Maps, for instance, uses crowd-sourced data to estimate traffic conditions on the suggested routes and then ranks the routes based on the estimated travel time. In addition to traffic conditions, the traffic light phases can also be considered inputs, as they play a significant role in increasing vehicles' and pedestrians' travel time.

An important aspect that may be accounted for is the energy toll or the carbon footprint (e.g., $CO_2$ emissions) associated with a given route. As an example, Green Light Optimal Speed Advisory (GLOSA) methods [8] suggest the optimal speed for cars, taking into account the phases of the traffic lights, so that cars can go through the intersection without stopping and, so doing, reduce $CO_2$ emissions. Similarly, Liu et al. [9] suggest a route planner that optimizes fuel consumption by factoring in the traffic light phases as one of its inputs. In addition to them, the route planner ought to prioritize routes according to the individual driver's preferences, which may include the number of traffic lights or roundabouts along the route, to improve the overall experience of commuting.

Augmented reality is one of popular applications of the Metaverse that requires low latency and large data rate, both of which can be provided by the V-Edge ecosystem [2]. In this context, it is interesting to note that vehicle route planners can also aim at optimizing the resources made available by vehicles or pedestrians on the virtual edges, as one of the factors to aid such Metaverse applications.

To this end, we propose a human-centered route planning system that meets both the needs of the driver and the needs of traffic flow. The proposed personalized vehicle route planner can take into account human behavior, state of alertness, and traffic-related information like traffic light phases, road works, and real-time congestion, to offer a better alternative for the vehicular user. Furthermore, the proposed framework uses driving and vehicle sensing data to estimate the drivers' behavior and level of attention in real time. In particular, during the route-selection process, the routes with less aggressive drivers are given higher preference to ensure people can travel safely. The driving style of the user requesting a route, instead, is used as a mean to estimate the need of the user for a short travel time towards the desired destination. On the other hand, the driver's attention level is used to recommend simple to complex driving routes, i.e., less attentive drivers will be assigned to routes with fewer turns and twists to avoid potential traffic accidents.

Real-time traffic information such as traffic light phases and congestion levels is obtained through the communication between vehicles and micro clouds. Micro clouds are formed by clustering the cars present on a road into groups to share the on-board storage, sensing, and computational resources with each other. In this way, the route planner can choose an optimal route with fewer cars and let a vehicle cross the intersection without waiting at the traffic lights for too long.

In addition, the route selection process relies on a complicated set of algorithms to choose the best route for the requesting vehicle, but, if the rationale behind the choice is not conveyed to the driver, people will less likely trust the selection process. This may happen in particular with local drivers, who prefer to take a different route in the early stages of adoption. Using an Explainable AI (XAI) strategy [10] is therefore necessary. Additionally, the proposed approach can educate commuters and help overcome their mistrust of AI models. Several are the strategies that can be enacted, including systems leveraging onboard dashboards and visual cues to demonstrate the reason for choosing a particular route to reach the destination.

## 3. Proposed Methodology

In the proposed human-centered route planning system, we achieve personalized and context-aware route planning by utilizing human behavior and real-time traffic data. The proposed system relies on two primary data sources: vehicle and environmental data. The vehicle-related data is required for the estimation of driving behavior and level of alertness, whereas environment-related data provides information on traffic signal phases, road congestion, and roadwork.

The architecture of the proposed human-centered route planning system includes the modules depicted in Figure 1 and detailed below.

*Vehicular data:* Modern vehicles are equipped with many sensors that can extract data pertaining to both internal and externally conditions, enabling the collection of comprehensive information. Particularly, the engine control unit logs every minute data, including acceleration, speed, yaw rate, pedal positions, and steering input. Furthermore, vehicles may have long- and short-range radars, cameras, and lidars to gather information about their surroundings. Importantly, wireless communication interfaces are currently being installed in vehicles to enable vehicle-to-everything (V2X) communication. Through such communication, vehicles can exchange sensory

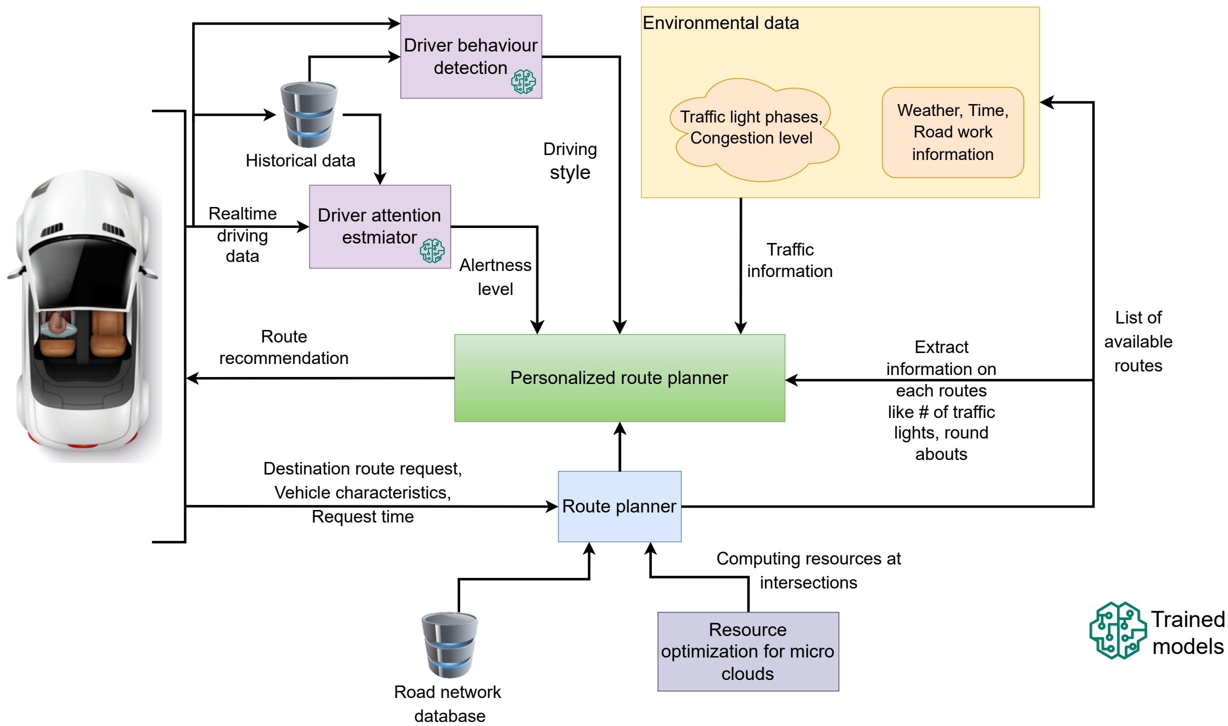


Figure 1. Human-centered route planning system: Route planner queries the road information database for the list of routes considering the destination location and service module request. Driver profiling is done with the help of driver behavior and attention level estimators. The dynamic data module provides the latest traffic-related information for the available routes. Personalized route planner gets input from all modules to provide the route that best suits the driver.

information and, doing so, extend their sensing horizon and achieve cooperative perception [11], [12].

The information received and generated onboard can then be stored aboard vehicles, leveraging the storage and computational capabilities with which they are equipped. These capabilities help a vehicle implement its ADAS-related applications, such as adaptive cruise control and lane-keeping assistance, to make driving safer and more comfortable for the driver [13]. In this suite of applications, we propose to use driver behavior and attention estimation to provide a personalized, context-aware route planning service by leveraging vehicle data.

*Driver behavior detection:* Detection of driver behavior is one of the key components of the proposed system, as it helps determine the risk associated with the driving style of the human being. We combine historical data with real-time vehicle data, as the momentary data alone is not sufficient to identify the driver behavior. In addition, we also gather the data of the surrounding vehicles using sensors such as radar or cameras. The reason for this is that, e.g., a high-speeding vehicle on a road where there are no other vehicles is not perceived as aggressive as it would be in a situation with other vehicles in the vicinity. Specifically, a proper machine learning (ML) model can be trained to determine the driver's behavior by utilizing acceleration, speed, headway, and traffic-related information as features. During the inference phase, the ML model will then provide a prudent driving score and an eager driving score, thus allowing the framework to assess how sensible the driving style of the human being is and how anxious the driver is to reach the desired destination.

*Driver attention estimator:* Similarly, the driver attention estimator helps the system to estimate driver fatigue level. The study by Sikander and Anwar [14] presents a comprehensive survey for the driver fatigue detection methods. In our system, we use such features as steering angle, lane wavering, and in-cabin camera to detect the driver's alertness based on real-time and historical data. For instance, the vehicle data with sporadic spikes on the steering wheel input indicates that the driver is not alert. The driver fatigue prediction assists in determining the difficulty of the recommended route for the driver. It also assists in distributing the possible route among multiple drivers in a balanced manner, as opposed to recommending the shortest route to everyone, which would result in a congested road network.

*Environmental data:* We collect environmental data via communication between vehicles and micro clouds established at intersections. The architecture of the vehicular micro cloud that we consider is shown in Figure 2. Similarly, vehicles at an intersection form a micro cloud to share resources and storage capacities, and to store information such as traffic light phases and congestion levels in a cooperative way. Thanks to data exchange with a micro cloud [15], the personalized route planner can acquire the environmental information that is necessary for efficient route planning. It is worth to highlight

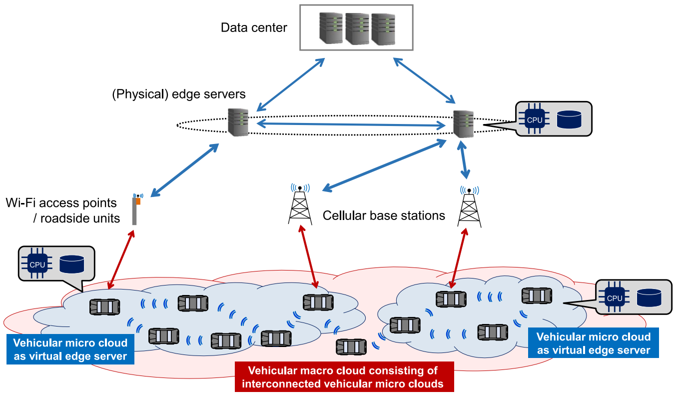


Figure 2. Vehicular micro cloud architecture [16]. Vehicles on the road form a cluster to share their storage and computation capabilities. Micro clouds act as virtual edge servers and have the ability to connect with physical edge servers and back-end data centers.

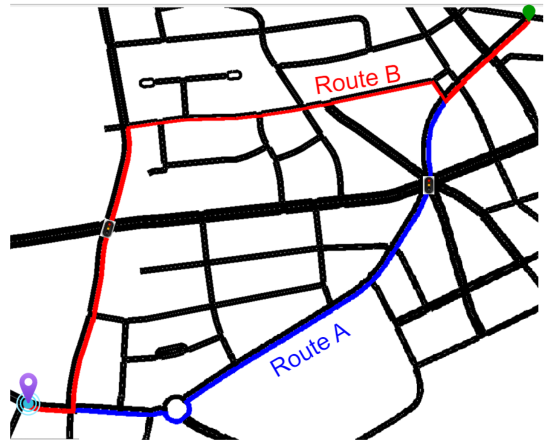


Figure 3. Different routes to reach the destination. Route B is better than Route A, as the latter exhibits longer traffic light phases despite Route A being the shortest one.

that a trade-off has to be made when deciding how far a micro cloud providing input information to the planner can be located. On the one hand, using information coming from micro clouds allows for the collection of more data and, hence, for a larger perception horizon. On the other hand, as the micro cloud is further away from the route request location, the situation reported by the micro cloud will likely change by the time the vehicle reaches the intersection where the micro cloud is operating. In this case, the information from a distant micro cloud may result to be ineffective for route planning. Finally, we remark that in the propose framework micro clouds provide not only traffic information, but also dynamic road-related information such as road construction, time-based route restrictions, and weather-related information.

*Personalized route planner:* The aim of the proposed framework is to personalize the route planner based on the preferences of the drivers, with the assistance of the modules that have been presented. Upon receiving a request from the vehicle to search for a route to a desired location, the road information database is queried to identify the best routes to reach the destination. The road information database contains comprehensive details about the nodes and edges of the road network. In addition, the route planner incorporates information from the micro cloud resource optimization module when querying the database for suitable routes [17]. The role of this module is to maintain adequate resources at each micro cloud. It will examine the computing resources available at each micro cloud in the road network and provide the route planner with information about them. It is an opt-in service in the proposed human-centered navigation system, which means that the user has the flexibility to choose whether or not to take part in it. The database is then queried to retrieve a list of available routes to the desired location. The environmental data module provides current traffic-related information for all available routes, including the current level of traffic congestion, the phases of the traffic lights, and the roadwork specified for each route. In addition, we extract information like the number of traffic lights, the number of turns, and the number of roundabouts on each route to estimate the degree of difficulty and travel time. Furthermore, the driver's behavior and attention estimator modules provide information regarding the driver's driving style and attention level based on current and historical data. The personalized route planner must consider the data from these modules when determining the optimal route for the driver to reach the destination. The planner must also be able to deal with data dynamics, especially if real-time data from traffic and vehicle sensors is affected by external factors. Given the complexity of the proposed planner, we leverage AI-based techniques that can deal with the inputs from multiple data sources. Finally, the driver and corresponding route information are then transmitted to the cloud storage for further processing.

With the proposed system, we intend to select routes based on the driver's preferences and traffic statistics, as opposed to choosing the most direct route to the destination. For example, the generic route planner would recommend route A in Figure 3 because it is the shortest distance. However, the traffic light phases are longer on route A than on route B, which makes the average waiting time at the intersection longer. As a result, the proposed system would select route B as a suitable route in this case, taking advantage of traffic-related information and offering a better traveling experience. On the other hand, Figure 4 illustrates the role of the micro clouds resource optimization module. When making micro clouds work efficiently is set as a priority, the vehicle would be routed through route A, in order to keep the micro cloud operational.

One of the main challenges of the proposed system is ensuring that drivers adopt the proposed routes. The study in [18] highlights that human drivers are typically unwilling to alter their route to avoid traffic congestion. Educating the user on the rationale behind the route change is a crucial factor in enhancing the rate of adoption of the proposed approach. Similarly, the rate of users willing to change the route to

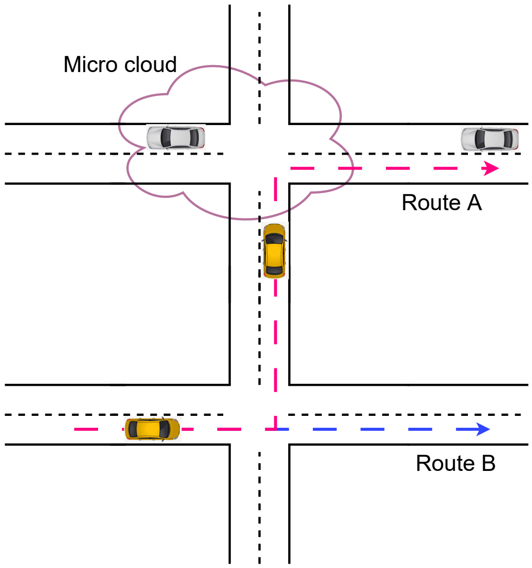


Figure 4. Resource optimization for micro clouds: Re-routing the vehicle to keep the data alive at the micro cloud.

optimize the micro clouds architecture may be low. Thus, a reasonable business model for this service has to be defined to motivate the user to be part of the resource optimization of the micro clouds.

## 4. Research challenges and Future Directions

The development of the human-centered navigation system aims to provide personalized and context-aware routing solutions to reach a destination preferred by the driver. Several challenges must be dealt with to envision such a navigation system. In this section, we discuss some of the significant difficulties associated with the proposed human-centered navigation system.

*1) Reliable Detection of Driver Behavior and Attention:* The proposed system has two main components, i.e., human driver behavior and an attention estimator, which are fundamental to accounting for human behaviors in achieving personalized and context-aware vehicle routing. These two components require carefully annotated datasets to train models that account for the driver's eye movements, facial expressions, location, vehicle movements, and surrounding environmental data for estimating the driver's attention and behavior. However, the creation of such models is difficult as it requires both hardware elements (a vehicle sensor array) and software abilities (CPU and GPU) to train and evaluate the models with this heterogeneous data. Furthermore, the proposed system also intends to ascertain the driver's eagerness to reach the destination in emergency situations. To properly train the model and correlate the driver's intent and behavior, the system requires datasets associated with the purpose of the trip and the time of the travel to ensure the driver is given the most efficient route in terms of time to reach their destination. Due to external factors such as the driver's age, experience, road traffic conditions, and emotional state that influence driving styles, it is challenging to formulate a generic model that incorporates all drivers. Given the intricate nature of gathering data, labeling it, and correlating it with diverse driving scenarios and drivers, further research is necessary to tackle these challenges and provide a robust solution.

*2) Externalities:* The development of an AI-based, human-centered traffic management system with the capability to collect and process real-time data of heterogeneous formats (images, videos, numerical) is a challenging task as it suffers from several external effects arising from the integration of various subsystems with different sampling periods and environmental aspects that can lead to data unavailability or erroneous data. In addition, the system also relies on the vehicular micro cloud to gather traffic-related information, such as traffic light phases. However, the vehicular micro cloud might not be available at all intersections, particularly during non-peak hours. To make the system resilient in such instances, the system needs to have an estimator that leverages past data to infer such information. In addition to data-related challenges, human preferences and desires sometimes lead them to deviate from the suggested route, presenting a difficult challenge to capture and model through the planner. The reluctance to trust automated systems is a significant hurdle to the more widespread adoption of these services. The development of a user-friendly, effective, and interactive in-vehicle Human-Machine-Interface (HMI) is essential for helping people overcome doubts about the proposed system and maximize the system's acceptance rate.

*3) Robust Route Planner:* The proposed human-centered route planner encompasses multiple sub-modules to consider human behavior, providing a tailored route for individuals. The route planner aims to utilize machine learning algorithms to analyze and interpret underlying data patterns, suggesting improved routes. Nevertheless, from the various ML paradigms, such as semi-supervised, unsupervised, and reinforcement learning, a suitable one has to be selected that can adapt to data dynamicity. It involves extensive testing and evaluation of different algorithms to ensure the accuracy and reliability of the system. One of the main challenges for the route planner is to factor in the importance of each module carefully when planning their route. For instance, an aggressive driver can be mistakenly identified as a driver who needs to reach their destination quickly. It would wrongly motivate aggressive drivers to use the system to their advantage, pretending to be eager drivers trying to reach their destination because of emergencies and receiving the fastest routes available, which would be detrimental to the proposed system. Furthermore, although the route planner prioritizes a user-centric experience, it must also consider the overall traffic flow to enhance network-wide improvements in traffic flow. The system additionally emphasizes resource optimization for the micro clouds, requiring a detour from the standard route. A comprehensive study is necessary to comprehend the influence of the detour on the change in time duration to reach the destination versus the optimization of micro cloud resources in order to determine whether the detour yields a substantial advantage. A detailed analysis has to be performed to determine the efficiency of the proposed system in finding new routes in a time-sensitive manner and to assess the feasibility of implementing the system in real-world scenarios.

*4) Explainable AI (XAI):* To further strengthen the proposed approach, a significant future research direction is to provide users with human-interpretable AI decisions. In general, data-driven models generated by AI-based algorithms are referred to as "black box" models because their outcomes are difficult to interpret. The primary objective of XAI is to provide interpretable AI decisions to end users by summarizing the results of "black box" models with human-comprehensible explanations, one of the main building blocks of the Metaverse [3]. In the proposed system, for instance, the change of the current route can be explained by showing visuals of traffic congestion in segments of the current route associated with the time required to reach the destination if the route is not adjusted according to the recommendations. Explaining the decisions made by data-driven models based on decision tree algorithms is relatively straightforward. During the inference phase, the decision tree algorithms begin at the root node and move through intermediate nodes based on specific conditions to reach the decision node or leaf node, based on the input data. It is possible to ensure the decision's explicability by examining the decision tree's path. However, input data with complex structures are typically trained using Deep Neural Networks (DNN), and the results of DNN models are harder to interpret. Therefore, techniques such as Layer-wise Relevance Propagation (LRP) [19] are utilized to explain the decisions made by the DNNs. The LRP technique determines the logic behind decisions by propagating each neuron's relevance value from its output to the respective input features. Utilizing such XAI strategies to explain the results increases the end user's trust in AI models and encourages them to adopt the data-driven model in their daily lives without hesitation.

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