Driving Assistance to Elderly Drivers in Rural Areas

A Technical Report Submitted to the Rural Safe Efficient Advanced Transportation (R-SEAT) Center and United States Department of Transportation

FINAL REPORT

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February 2025

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TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Driving Assistance to Elderly Drivers in Rural Areas		5. Report Date 02/24/2025
		6. Performing Organization Code
7. Author(s) Ruwen Qin https://orcid.org/0000-0003-2656-8705 Ke Li https://orcid.org/0009-0001-4958-3302 Chenyu Zhang https://orcid.org/0000-0003-2500-5070		8. Performing Organization Report No.
9. Performing Organization Name and Address Stony Brook University		10. Work Unit No. (TRAIS)
		11. Contract or Grant No. 69A3552348321
12. Sponsoring Agency Name and Address Rural Safe Efficient Advanced Transportation (R-SEAT) Center 2525 Pottsdamer Street Tallahassee, FL 32310		13. Type of Report and Period Covered Final Report Period Covered: 02/22/2023 – 12/31/2024
		14. Sponsoring Agency Code
15. Supplementary Notes		

16. Abstract

This project investigates the mobility and safety challenges of elderly drivers in rural areas. Using data from the 2017 National Household Travel Survey (NHTS), we found that rural seniors need to travel longer distances for healthcare and to assist others, but are limited by age-related declines in vision, cognition, and motor skills, reducing their mobility and so access to resources. Further analysis showed that elderly drivers in rural areas experience higher fatal crash density and fatality rates due to aging-related challenges and higher speeds in rural areas, highlighting the need for targeted safety interventions. To address these challenges, we explored vision-based assistance for both human drivers and autonomous vehicles at various levels of automation. A novel teacher-student network was developed to handle multi-label image classification, overcoming data sparsity by learning from seven single-label datasets. This approach demonstrated that the multi-label classification model trained on single-label data perform similarly to dedicated single-label classification models. The project supports the development of visual intelligence technologies for elderly drivers and emphasizes the need for further research in rural settings.

17. Key Words	18. Distribution Statement
Elderly drivers, driving assistance, data analysis, deep learning, multi-label scene classification	No restrictions

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	42	

ACKNOWLEDGEMENTS

This project was sponsored by the Rural Safe Efficient Advanced Transportation (R-SEAT) Center and United States Department of Transportation. The Principal Investigators would like to thank the representatives of the R-SEAT Center for their valuable feedback throughout the project activities.

EXECUTIVE SUMMARY

This project investigated the mobility challenges and safety concerns of elderly drivers in rural areas through a series of studies. Our findings highlight the critical need for advanced driver assistance to enhance mobility, safety, and access to essential resources for this vulnerable population.

The project began by examining accessibility challenges faced by seniors in rural areas using data from the 2017 National Household Travel Survey (NHTS) and a proposed causal model. The analysis revealed that rural seniors have more needs to travel longer distances for healthcare and to assist others with transportation compared to their younger counterparts. However, their heavy reliance on automobiles, combined with age-related declines in perception, cognition, and motor execution, has reduced their mobility. Enhancing their ability to drive safely despite age-related challenges is crucial to ensuring rural seniors have adequate access to essential resources.

The project further examined elderly drivers' ability to drive safely. While they benefit from extensive driving experience and lower traffic congestion, age-related challenges, combined with generally higher speeds in rural areas, increase their vulnerability. Using a data fusion approach, the study assessed the impact of age and rural residency on fatal crash density and analyzed contributing factors, including fatality rate, injury rate, and overall crash density. The results confirm that vulnerability, as indicated by fatal crash density, increases with age among seniors, and the fatality rate for elderly drivers in rural areas is significantly higher than in urban areas. These findings highlight the urgent need for targeted safety interventions. Advanced driving assistance that helps prevent crashes and reduce fatality rates when collisions are unavoidable could make a significant impact.

Since vision is the primary sensory modality for safe driving and elderly drivers experience declines in visual perception and cognition, the project advanced its study to explore vision-based assistance for both human drivers and automated driving systems at various levels of automation. Among the many functions of visual intelligence, situational awareness presents unique challenges. Driving scenes are complex and dynamic, characterized by multiple attributes, making scene identification a multi-label image classification problem. However, the distribution of driving scenes in the high-dimensional space of scene attributes is highly imbalanced, making it infeasible to create a sufficiently large multi-label scene dataset for directly training a desired classification model. To address this data challenge, the study proposed an approach to acquire and accumulate knowledge about scene identification by leveraging seven single-label image datasets. A learning framework of teacher-student networks was developed, enabling sequential and cyclic learning across these datasets through single-task learning. Numerical experiments confirmed the feasibility of this approach, demonstrating that the resulting multi-label classification model achieved accuracy comparable to seven dedicated single-label classification models.

The project provides the data evidence to support the development of innovative visual intelligence technologies to assist elderly drivers in rural areas and help overcome their vision limitations. It also illustrates an exploration of computational methods to address data sparsity in rural areas. The lack of well-annotated big data in rural settings remains a challenge. Future research must focus on ensuring these technologies perform as effectively in rural areas as they do in urban environments.

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1. INTRODUCTION

This section provides the background information and context for the research project on Driving Assistance to Elderly Drivers in Rural Areas.

1.1. Elderly Drivers in Rural Areas

In the United States, rural residents heavily rely on automobiles for transportation. 96% of rural households have one or more vehicles. 94% of women aged 65 to 74 in rural areas drive, and this percentage is 79% for women aged 75 to 84, and 54% for women aged 85 or older (McGuckin and Fucci, 2018). The percentage of senior males in rural areas who drive is higher than that of females in the same age group. For example, 72% of males aged 85 or older in rural areas drive. According to a study, senior people continue driving because of lacking alternative means of transportation, and they start limiting their driving or stopping driving because of functional difficulties. On a short run, senior residents in rural areas still heavily rely on driving their personal vehicles. Assisting this group of drivers in rural areas is imperative to ensure their mobility and thus the quality of their lives.

Vision provides at least 85% of information we need to make safe decisions when driving. However, a 60-year-old person requires 10 times as much light to drive as a 19-year-old. A 55-year-old takes eight times longer to recover from glare than a 16-year-old. Senior drivers can take twice as long to distinguish the flash of brake lights as younger drivers. Besides the difficulty in seeing, stiff joints and weaken muscles, trouble hearing, slower reaction time and reflexes are other reasons that make it difficult for senior people to drive (Cicchino and McCartt, 2015; NHTSA, n.d.). Driver assistance technologies, especially from the aspect of visual perception and cognition, can help enhance the speed and accuracy of elderly drivers in response to risky traffic agents and dangerous scenarios. The desired technologies will enhance the safety and mobility for elderly drivers and other vehicle occupants in rural areas.

1.2. Gaps and Project Objectives

The long-term goal of this project is to create new driver assistant technologies for improving the mobility and safety of elderly drivers and their passengers in rural areas, a group of people who require specialized visual driving assistance in their daily driving activities. The needs for driving assistance among rural seniors are widely discussed, and commercialized driving assistance systems exist. However, research and development of modern assistive technologies dedicated to this unique group will benefit from a verification and deep understanding of the reduced mobility and safety among elderly drivers. Motivated by this desire, the project aims to accomplish the following objectives:

1. Evaluate the reduced mobility of seniors in rural areas and determine its impact on their access to essential resources
2. Analyze the vulnerability of elderly drivers in rural areas and determine the underlying causes
3. Identify compelling challenges in developing visual assistance systems for elderly drivers and explore solution approaches

We speculate that insights into the research problems can be gained from the National Household Travel Survey (NHTS) Dataset, the National Highway Traffic Safety Administration (NHTSA)'s safety databases, and driving video datasets.

1.3. Project Relevance to the REAT Themes and USDOT Strategic Plan

As a REAT-funded study, this project contributes new knowledge and methods that support the technology development for improving the safety and mobility of vulnerable road users in rural areas. The project well supports USDOT priorities and RD&T strategic goals, especially on the dimensions of safety. The project will identify concerns with the mobility, accessibility, and safety of seniors in rural areas through comparisons with their counterparties in rural areas and at different ages. Given the knowledge gained from data analysis, the project put an emphasis on innovating methods to overcome challenges in developing visual perception and cognition models in supporting elderly drivers. The methodological development is transformative, leading to impactful use of datasets maintained by USDOT and public datasets contributed by the research community.

1.4 Organization of the Report

This report is organized to guide the readers through the project's major activities. In the next section, the report presents the causal modeling and extracted data evidence for evaluating the mobility of seniors living in rural areas. Following that, Section 3 summarizes the data analysis for determining the vulnerability of elderly drivers. Upon the insights learnt from these two sections, Section 4 further presents a proposed method in addressing an impressing challenge in creating situational awareness in complex driving scenes. In the end, Section 5 summarizes major findings and outputs from this project.

2. MOBILITY OF SENIORS IN RURAL AREAS

Seniors residing in rural areas often encounter limited accessibility to opportunities, resources, and services. This section introduces a study that assumes both aging and rural residency are causal factors for the restricted accessibility faced by rural seniors. The study uses data analysis and causal modeling to examine if mobility is a moderator of the causal relationship. Contents of this section has been published as a conference paper (Li et al. 2024).

2.1 Background

People have unequal accessibility to spatially distributed opportunities, resources, and services that they intend to reach. Seniors living in rural areas are a group of people with more restricted accessibility for multiple reasons. To promote accessibility for this group, it is important to identify the root causes for their reduced accessibility. Compared to younger adults (aged 16 to 64) in rural areas, rural seniors have inherently different needs to access spatially distributed destinations. For example, a local clinic may no longer meet their special need for medical services. Due to the lower population density in rural areas, the cost for rural seniors to access certain destinations is more expensive than their counterparts in urban areas. That is, aging and rural residency are part of the reasons for the reduced accessibility of rural seniors. Aging and rural residency may influence people's accessibility through other causal pathways too. For example, some rural seniors cease driving once it becomes impractical. Their heavy reliance on automobiles and the increased restriction for them to choose this transportation mode also reduce rural seniors' accessibility. That is, mobility is part of a causal pathway, and it is a mediator of the causal relationship to be studied in this paper. Ignoring this causal pathway may underestimate the impact of aging and rural residency to the accessibility of rural seniors.

The study in Section 2 aims to determine how aging and rural residency negatively impact rural seniors' accessibility via multiple causal pathways and verify if mobility is a mediator. The 2017 National Household Travel Survey (NHTS 2017) dataset was used by this study, which is the only source of national data to study personal travel behavior. However, related work indicates that the selection of metrics for accessibility and mobility is affected by the study context and data availability. Therefore, discussions in this paper are driven by the following two questions. What metrics of accessibility and mobility can be derived from the NHTS dataset? What evidence can be found in this dataset to verify the assumed causal relationship?

2.2 Related Work

The literature relevant to this study includes research focused on developing indicators or measures for mobility and accessibility, determining their relationship with topological features, and examining the challenges faced by rural seniors.

2.2.1 Accessibility and Mobility

Accessibility is usually defined as the ability to reach the intended destinations (Litman 2003). According to Geurs and van Wee (2004), the four components contributing to accessibility encompass transportation, land use, individual factors, and time cost. Nonetheless, incorporating all these components as direct indicators of accessibility is challenging (Pyrialakou et al. 2016). Boisjoly and El-Geneidy (2017) reviewed various travel accessibility indicators such as the count of accesses to specific purposes within a defined time frame, which are influenced by factors like land use, opportunity distribution, and mobility. They also introduced two location-based measures of accessibility, namely the gravity-based measure and the cumulative opportunity measure. These measures have reached a level of maturity, extensively discussed in numerous research papers (El-Geneidy and Levinson 2006, Scott and Horner 2008, Casas 2007).

Mobility is defined as the movement of people and goods (Litman 2003). This concept underscores the act of movement rather than a mere means to a destination. Mobility was assessed using travel surveys to quantify person miles, ton-miles, and travel speeds. Furthermore, traffic data were utilized to gauge the average speeds of both automobiles and transit vehicles (Litman 2003). Mobility cannot be measured by a definitive or singular metric (Pyrialakou et al. 2016). Therefore, multiple indicators were developed, including travel mode distribution, travel frequency, and vehicle ownership (Pucher and Renne 2005; Jansuwan et al. 2013). To assess transportation disadvantages related to mobility, Kamruzzaman and Hine (2011) developed a comprehensive indicator called "participant index" (PI). It combines various elements, including the number of destinations visited, travel distance, space, travel frequency, types of activities, and duration. The mobility of individuals who do not drive can be enhanced by improved public transit infrastructure, reduced time required to reach transit stations, and increased proximity to their intended destinations (Case 2011).

Transportation network topological features play a significant role in determining the efficiency in low-volume roads, especially in rural area, from a micro perspective. Connectivity and node accessibility measures, which are integrated in the accessibility concept, are introduced to evaluate topological accessibility (Garrison 1960). Labi et al. (2019) presented three models of connectivity, accessibility, and mobility (CAM) relationship. The overall impact of CAM was considered in their proposed basic classification of measures. Sarlas et al. (2020) proposed betweenness-accessibility, a centrality measure allowing to quantify accessibility from a network-based view. Thus, measures can be dedicated to spatial analysis, vulnerability analysis, and cost-benefit analysis.

2.2.2 Seniors in Rural Areas

Martens (2015) introduced a framework for assessing accessibility offered by a transport-land use system and the potential mobility facilitated by the transport system. This study indicated that the improved accessibility is partially attributed to the enhanced mobility. Actually, mobility data were employed to assess accessibility (Mittal et al. 2023). However, the popularly used gravity-based measurements do not adequately account for the influence of mobility on accessibility. Both mobility and proximity play pivotal roles in enhancing accessibility, but they often exist in a trade-off relationship (Grengs et al. 2010). In areas where the origin and the destination are close (high proximity), travel speeds typically tend to be slower (low mobility). Therefore, accessibility measures should consider the combined influence of location- and mobility-related factors.

Rural seniors have varying challenges due to their demographic characteristics. For example, "young elderly" (aged 65-75) and the "old elderly" (aged 75+) have different travel patterns and expectations on accessibility (Alsnih and Hensher, 2003). When aiming to enhance the accessibility of seniors, it is imperative to consider their mental and physical needs. Accessibility varies significantly among different groups of travelers, such as individuals with mobility impairments attributed to aging and those reliant on public transit (Márquez et al. 2019). In the

United States, automobiles are the predominant travel mode in rural areas (Pucher and Renne 2005), and seniors particularly rely on automobiles for travel (Kim 2011). Rural seniors' mobility for daily travel needs is restricted when it comes to public transit and walking (Ravensbergen et al. 2021). Rural areas are typically less developed than urban areas from the view of accessibility to opportunities, resources, and services (Vitale Brovarone and Cotella 2020).

2.3 The Method

2.3.1 Hypotheses About the Causal Relationship

This paper posits a causal relationship wherein the attributes of rural seniors are factors (i.e., independent variables) causing reduced accessibility (i.e., the dependent variable). While the interested relationship has multiple causal pathways, this paper examines two, as shown in Figure 1. The first causal pathway goes directly from the group's attributes to its accessibility. In the second pathway, the attributes impact accessibility via mobility, a mediator variable. Three hypotheses delineated in Figure 1 are underlying this causal relationship:

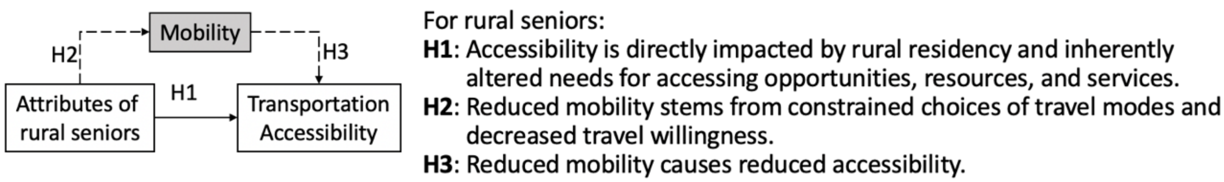

Figure 1. The proposed causal model of accessibility for rural seniors

2.3.2 The NHTS Dataset

This study examined the hypothesized causal relationship in Figure 1 by extracting evidence from the 2017 National Household Travel Survey (NHTS 2017). This dataset contains a completed survey from 129,696 households and 923,572 person trips. We defined the scope of data analysis by concentrating on four primary travel modes (automobiles, bicycles, walking, and public transit), six key travel purposes (home, work, medical service, shopping, recreational activities, and transporting someone), and local travel with distance being within 75 miles.

2.3.3 Attributes and Measures

Attributes or measures are defined for examining the influences among variables in the causal model. Age and residency area are selected as the demographic attributes for characterizing travelers. We define adults 16~64 years old as Yadults and those aged 65 or older as senior. Comparing rural seniors to rural Yadults facilitates the measurement of aging-induced changes, while comparing them to urban seniors allows for the measurement of location-induced changes. This study chose travel distance and travel time to intended destinations as measures of accessibility. Because both are random variables, their 75th percentiles conditioned on a specific travel purpose are used as indicators of the ease to reach an intended destination. This study chose four indicators as the basis for evaluating mobility, including the distribution of trips by travel modes, travel frequency, travel speed, and time to access public transit stations. Notably, travel frequency, often expressed as the number of trips per person per day, is the principal indicator for measuring mobility in numerous prior studies (Pucher and Renne 2005, Szeto et al. 2017). Although factors like congestion and travel miles per person also hold significance for assessment

(Litman 2003), this study selected travel speed and time to access public transit considering the data coverage of NHTS.

2.4 Analysis and Discussions

2.4.1 The Direct Impact of Rural Residency on Accessibility

Hypothesis H1 asserts that the increased travel distance for rural seniors to reach their intended destinations, in contrast to their urban counterparts, is a contributing factor to their reduced accessibility. To verify this hypothesis, this study compared rural seniors to urban seniors on their cumulative distribution functions (CDFs) of travel distance, $F_{D,RSr}(x)$ and $F_{D,USr}(x)$, for each specific travel purpose. These two groups were also compared in terms of their travel time CDFs, $F_{T,RSr}(x)$ and $F_{T,USr}(x)$. Statistics of travel time and travel distance are further summarized in Table 1.

Table 1. Statistics of travel distance and travel time by groups and travel purposes

	$D_{0.5}$ (mile)			$D_{0.75}$ (mile)			$T_{0.5}$ (min)			$T_{0.75}$ (min)		
Purpose	RSr	RYa	USr	RSr	RYa	USr	RSr	RYa	USr	RSr	RYa	USr
Home	7.2	8.2	2.7	14.1	16.0	6.2	15.0	16.0	15.0	30.0	30.0	25.0
Work	7.7	9.4	4.4	16.0	19.4	10.3	15.0	18.0	15.0	30.0	30.0	30.0
Medical	13.3	12.1	5.0	22.9	20.4	11.2	30.0	23.0	20.0	45.0	32.0	30.0
Shopping	4.3	4.1	2.3	10.6	10.4	4.8	12.0	10.0	10.0	20.0	20.0	17.0
Recreational	4.7	5.7	3.1	11.2	13.8	7.9	15.0	15.0	15.0	17.0	30.0	25.0
Transport someone	7.0	6.0	3.6	14.9	11.3	7.9	15.0	15.0	15.0	30.0	20.0	21.0

Note:
RSr: Rural seniors; RYa: Rural Yadults: USr: Urban seniors
$D_{0.5}$ (mile): 50th percentile of travel distance; $D_{0.75}$ (mile): 75th percentile of travel distance
$T_{0.5}$ (min): 50th percentile of travel time; $T_{0.75}$ (min): 75th percentile of travel time

Within a specific travel distance, $F_{D,RSr}(x) < F_{D,USr}(x)$ for all the travel purposes of study. That is, rural seniors can access fewer intended destinations than their urban counterparts within the same travel distance. For example, within 15 miles rural seniors reach 52.8% of their destinations for medical services, whereas this percentage for urban seniors is 82.9%. Similarly, given a specified travel time limit, $F_{T,RSr}(x) < F_{T,USr}(x)$ for the purposes of going home, accessing medical services, shopping, and transporting someone. That is, rural seniors experience drawbacks while accessing intended destinations than their counterparts in urban areas within the same travel time. For example, rural seniors reach 69.0% of their shopping destinations within 20 minutes, whereas urban seniors can reach 76.1%. Differences in their travel distance and travel time distributions are verified by the Kolmogorov-Smirnov (KS) test (p-value = 0).

Hypothesis H1 also states that aging is a factor that alters the intended destinations of rural seniors, which in turn changes their accessibility. To determine the direct impact of aging on accessibility, rural seniors were compared to rural Yadults with respect to their travel distance and travel time. For work commute, home returning, and recreational activities, $F_{D,RSr}(x) > F_{D,RYa}(x)$ at any given travel distance, and $F_{T,RSr}(x) > F_{T,RYa}(x)$ at any given travel duration. Those distinctions were verified by the KS test (p-value=0). For example, the observations pertaining to the purpose of work commute indicate that rural seniors intend to take job opportunities that are spatially and temporally closer to their homes than Yadults in rural areas. Rural seniors are supposed to travel for a longer distance to access medical services, as compared to rural Yadults. For example, the 75th percentile travel distance to medical services is 22.9 miles for rural seniors and 20.4 miles for rural Yadults, as shown in Table 1. The difference in their travel distance CDFs was further verified by the KS test (p-value = 0.22), suggesting that these two groups have a moderate level of difference in travel distance to medical services. We conjectured that rural seniors may require special medical services more likely at farther destinations (e.g., in urban areas with well-developed medical services), but not for Yadults. Furthermore, in contrast with Yadults, rural seniors also have to travel for a longer time to access intended medical services. For example, Table 1 shows that 75% of rural seniors' trips to medical services are within 45.0 minutes, but it is 32.0 minutes for rural Yadults. The results indicate a restraint on accessing medical services for seniors than Yadults in rural areas both from the travel time and travel distance aspects.

For transporting someone, the discrepancy in travel distance CDFs between seniors and Yadults in rural areas is statistically significant (p-value of KS test is 0). Table 1 further shows the 75th percentile travel distance for rural seniors is 14.9 miles, whereas it is 11.3 miles for rural Yadults. Meanwhile, the difference in travel time between these two groups is also evident. The longer travel distance and travel time for rural seniors to transport someone to intended destinations is probably associated with the fact that rural seniors are more available than rural Yadults in providing transportation to others whose intended destinations are farther from their homes.

In summary, rural seniors encounter restricted accessibility for accessing medical services and assisting others. Nevertheless, it is noteworthy that they do not face equivalent limitations in activities such as returning home, work commute, shopping, or recreational pursuits. This distinction can be attributed to the special needs and willingness of this group to access some services or resources.

2.4.2 The Impact of Aging and Rural Residency to Mobility

The hypothesis H2 asserts that the reduced mobility among rural seniors stems from more restricted choices of their preferred transportation modes. In verifying this hypothesis, the study first analyzed the distribution of trips by transportation modes and traveler groups, as shown in Table 2. The marginal distribution of trips by transportation modes shows that automobiles are the most preferred mode, fulfilling 89.01% of trips. The frequency distribution of trips by transportation modes varies among the three groups according to the chi-squared contingency test (p-value=0). Rural seniors heavily rely on automobiles, which are used for 93.9% of their trips (=10.45%/11.13%). Walking is the secondary transportation mode for rural seniors, which fulfills 5.1% (=0.57%/11.13%) of their trips. Other modes count for an almost negligible amount. Although automobiles are still the primary transportation mode for urban seniors, the percentage of trips via automobiles is 84.3% (=38.32%/45.48%), 10.2% less compared to rural seniors. Besides automobiles, walking and transit are also their choices, which count for 11.3% (5.14%/45.48%) and 3.4% (=1.53%/45.48%) of their trips, respectively. What's more, the frequency of the trips among the transportation modes is similar between rural Yadults and rural seniors except that the former has a slightly lower proportion (92.8%) of trips using automobiles and a sensibly higher proportion (0.7%) of trips by transit. The heavy reliance on automobiles exposes rural seniors to the risk of compromised mobility when driving becomes unsuitable for them and fewer people can provide transportation to them.

Table 2. Distribution of trips by transportation modes and groups

	Automobile	Walking	Transit	Bicycle	Others	Total
Rural Seniors	10.45%	0.57%	0.04%	0.01%	0.06%	11.13%
Rural Yadults	40.25%	2.24%	0.32%	0.14%	0.45%	43.39%
Urban Seniors	38.32%	5.14%	1.53%	0.24%	0.25%	45.48%
Total	89.01%	7.95%	1.90%	0.39%	0.75%	100.00%

The study further calculated the measures of mobility, including travel frequency, travel speed, and time to public transit, for the three groups of travelers, which are summarized in Table 3. From the table, one can find that rural seniors have an average of 2.98 trips per person per day, the lowest among the three groups. The low travel frequency of rural seniors indicates a lower level of willingness they possess for travel. The travel speed of rural seniors is higher than urban seniors, which is attributed to the fact rural seniors are usually farther from their intended destinations than their counterparts in urban areas (Pucher and Renne 2005), which necessitates high-speed travel. However, the travel speed of rural seniors is lower than rural Yadults, evident that aging negatively influences rural travelers' mobility. The faster travel speed of seniors in rural areas than people in urban areas should not lead to the conclusion that mobility is higher in rural areas. Recognizing the constrained transportation choices and the restricted availability of public transit services for residents in rural areas is essential. This circumstance consequently amplifies the predominant reliance on automobiles in rural areas. Surprisingly, rural seniors require less time to reach transit stations, with an average of 7.29 minutes, in contrast to the other groups. It may seem contradictory to our initial hypothesis. However, rural seniors demonstrate a reduced preference for public transit (see Table 2). This shorter average time to the public transit pertains to only a small portion of trips.

Table 3. Measures of travel mobility

	Frequency (per person per day)	Travel speed (mph)			Avg. time to public transit (min)
		Automobile	Public transit	Non-motor	
Rural Seniors	2.98	27.6	19.2	5.7	7.29
Urban Seniors	3.24	20.0	11.6	3.8	7.85
Rural Yadults	3.31	30.8	21.7	6.2	10.89

In summary, aging and rural residency have been factors contributing to the reduced mobility among rural seniors. Aging is the main reason for the decreased travel frequency, and the lower density of opportunities, resources, and services in rural areas leads to their reliance on automobiles. Although automobiles meet their need for fast-speed travel, the heavy reliance on this mode without alternatives will cause a mobility crisis for this group if this preferred travel mode becomes infeasible.

2.4.3 The Impact of Mobility on Accessibility

Hypothesis 3 assumes that a higher level of travel mobility effectively increases accessibility, which is well discussed in the literature. This study attempted to verify this relationship using the 2017 NHTS dataset. Table 4 presents the 75th percentiles of travel distances, travel times, and travel speeds for the four travel modes associated with different travel purposes. Statistics in the table indicate long-distance trips rely on automobiles and public transit and, walking and riding bicycles are chosen for trips within short distances. The variation of trip distance CDF across those travel modes is further verified by the KS test (p-value=0).

Table 4. Statistics of travel distance, travel time, and travel speed by transportation modes and travel purposes

	$D_{0.75}$ (mile)				$T_{0.75}$ (min)				$S_{0.75}$ (mph)			
Purpose	Walk	Bicycle	Auto	Transit	Walk	Bicycle	Auto	Transit	Walk	Bicycle	Auto	Transit
Home	1.0	2.6	10.6	10.6	26.0	30.0	25.0	60.0	3.3	7.8	31.3	14.0
Work	0.6	3.2	15.6	14.0	15.0	30.0	30.0	60.0	3.4	8.7	35.9	15.9
Medical	0.6	2.2	13.5	7.8	15.0	25.0	30.0	60.0	2.8	6.5	31.9	12.6
Shopping	0.5	1.5	6.7	7.2	15.0	25.0	18.0	50.0	3.2	6.0	27.7	12.4
Recreational	0.8	2.5	11.5	9.9	19.0	30.0	27.0	46.0	2.0	9.4	32.8	15.5
Transport someone	0.6	1.2	8.4	9.0	15.0	15.0	20.0	45.0	3.2	7.5	30.4	19.7

Note:
$D_{0.75}$:75th percentile of travel distance; $T_{0.75}$:75th percentile of travel time; $S_{0.75}$:75th percentile of travel speed

While automobiles and transit are both options for long-distance trips, the former offers a higher level of mobility than the latter. The 75th percentile speed of automobiles is at least twice of the transit for all purposes except for transporting someone, and the 75th percentile travel time of automobiles is 41%~64% less than the transit. Automobiles move travelers to farther destinations of work, medical services, and recreational facilities than the public transit does, which is probably attributed to the higher level of mobility with automobiles. Notably, the 75th percentile travel distance to medical services via automobiles is 13.5, but it is 7.8 for the transit. Yet, for the purposes of shopping and transporting someone, the transit moves people to their slightly farther (0.5~0.6mi) destinations than automobiles. Table 2 shows that trips via automobiles are 89.01% whereas those via public transit are 1.9%. The distinctly different proportions of trips by those two transportation modes are probably a result of the public transit's lower level of mobility than automobiles.

While walking and riding bicycles are both short-distance transportation modes, the latter offers a higher level of mobility than the former. The 75th percentile speed of riding bicycles is 88%~370% faster than walking. Consequently, bicycles move travelers to destinations 100%~433% farther than walking. However, Table 2 shows only 0.39% of trips use bicycles, significantly lower than walking (7.95%).

To sum up, automobiles offer the highest level of mobility among the four transportation modes, making it the dominating mode of transportation in the United States for all travel purposes. Transit, as an alternative to automobiles for long-term travel, offers a lower level of mobility and thus transports travelers to closer destinations for certain travel purposes like accessing medical services. Riding bicycles provides a higher level of mobility than walking for short-distance travels, bringing travelers to farther destinations at a faster speed than walking can reach. However, the proportion of trips by riding bicycles is significantly lower than walking, indicating certain constraints such as biking infrastructure prevent travelers from switching from walking to riding bicycles. The observations underscore the fact that the higher level of service road system and the mass rapid transit system can improve mobility and, in turn, accessibility.

2.4.4 The Impact of Aging and Rural Residency to Accessibility via Mobility

The hypotheses H2 and H3 together indicate that mobility is a mediator on a causal pathway illustrated in Figure 1. That is, aging and rural residency of travelers raise mobility issues, which in turn limit rural seniors' accessibility to certain desired opportunities, resources, and services. This study further verified the mediator role of mobility by examining the travel distance and travel time of the three traveler groups under selected combinations of travel purposes and transportation modes. Table 5 summarizes the 75th percentiles of travel distance and travel time.

Table 5. Statistics of travel distance and travel time, by combinations of transportation modes and travel purposes among rural seniors (RSr), rural Yadults (RYa), and urban seniors (USr).

	Shopping						Medical Service						Transport Someone			
	Walk		Auto		Transit		Walk		Auto		Transit		Auto		Transit	
	$D_{0.75}$	$T_{0.75}$	$D_{0.75}$	$T_{0.75}$	$D_{0.75}$	$T_{0.75}$	$D_{0.75}$	$T_{0.75}$	$D_{0.75}$	$T_{0.75}$	$D_{0.75}$	$T_{0.75}$	$D_{0.75}$	$T_{0.75}$	$D_{0.75}$	$T_{0.75}$
RSr	0.34	10.0	10.8	20.0	17.2	40.0	0.4	15.0	22.2	45.0	22.2	55.0	14.9	30.0	19.0	50.0
RYa	0.58	20.0	10.5	20.0	14.0	27.0	5.1	25.0	20.6	34.0	15.0	26.0	11.6	20.0	4.3	15.0
USr	0.44	15.0	5.2	16.0	4.7	48.0	0.7	20.0	11.9	30.0	10.3	50.0	8.1	22.0	16.5	45.0

Note:
$D_{0.75}$:75th percentile of travel distance (mile) ; $T_{0.75}$:75th percentile of travel time (min)

This study found that rural seniors need to access a larger percentage of medical services that are at farther distances and require a longer time to reach than rural Yadults and urban seniors. Table 5 shows that their 75th percentile travel distance to medical services using automobiles is 22.2 miles and the 75th percentile travel time is 45 minutes. These statistics are 20.6 miles and 34 minutes for rural Yadults and 11.9 miles and 30 minutes for urban seniors. The comparison indicates that automobiles, as a dominating transportation mode, offer a lower level of mobility for rural seniors in accessing medical services than for other groups. Rural seniors also undertake longer travel distance ($D_{0.75} = 22.2$) and time ($T_{0.75} = 55.0$) to access medical services if taking transit, due to its limited mobility for this group. Simultaneously, walking is also a transportation mode with a reduced level of mobility for rural seniors than their counterparts. The 75th percentile of travel distance is 0.4 miles and the 75th percentile of travel time is 15 minutes for rural seniors, whereas those statistics are 5.1 miles and 25 minutes for rural Yadults; and 0.7 miles and 20 minutes for urban seniors. Improving the mobility level of automobiles and transit for rural seniors would provide them with more accessibility to medical services as compared to others.

The final focus of understanding mobility as a mediator centers on the purpose of transporting others. As found from the study of H1, rural seniors have a higher percentage of trips that spend longer time and travel for a longer distance to reach the destinations for assisting someone than rural Yadults. This difference is particularly distinct in using the transit. Table 5 shows the 75th percentile of travel distance is 19.0 miles and the 75th percentile of travel time is 50.0 minutes for rural seniors, and those statistics are 4.3 miles and 15 minutes for rural Yadults. Rural Yadults demonstrate different behavior than seniors in choosing transportation modes for transporting others, indicating the mobility levels of automobiles and transit are different among these groups. Meanwhile, the significant distinction between rural seniors and urban seniors is from the utilization of automobiles. As shown in Table 5, the 75th percentile of travel distance is 14.9 miles, and the 75th percentile of travel time is 30.0 minutes for rural seniors, but 8.1 miles and 22.0

minutes for urban seniors. This varying accessibility is attributed to fewer travel mode alternatives to automobiles. Specifically, poor public transit facilities and low-density distribution of opportunities, resources, and services in rural areas lead to the heavy reliance on automobiles.

In summary, mobility is a mediator through which aging can lower rural seniors' accessibility. Automobiles, as the dominating transportation mode for long-distance travel, offer a lower level of mobility to rural seniors than rural Yadults, especially in accessing medical services and transporting others. Walking is the major mode for short-distance movement, but it prevents rural seniors from accessing destinations that are a little farther and accessible by rural Yadults or urban seniors. Rural seniors have limited choices of transportation modes, for both long-distance and short-distance travel, making it more difficult to reach intended farther destinations.

2.5 Summary of the Mobility Study

This study presented a causal model delineating both the direct and indirect effects of aging and rural residency on travelers' accessibility to opportunities, resources, and services. In this model, mobility serves as a mediator through which the demographic attributes of rural seniors indirectly influence their accessibility. Descriptive statistics of the trip data in 2017 National Household Travel Survey support our hypotheses, confirming the presence of the proposed causal relationships.

An immediate step following this study is to estimate the coefficients that quantify the strengths and directions of the causal relationships. Given such a model, the effectiveness of improving accessibility for rural seniors by enhancing their mobility can be estimated. Additionally, the causal model can be further improved by integrating additional causal relationships. Beyond aging and rural residency, various additional factors, such as land use, traffic congestion, opportunity density, and infrastructure density, impact travel mobility and accessibility. It is worth noting that using distance to evaluate accessibility has limitations due to the effect of distance decay, which represents the level of reluctance to travel long distances among regions. Future studies could explore modified indicators for accessibility and refine the construction of a comprehensive causal model to address these considerations.

3 THE VULNERABILITY OF ELDERLY DRIVERS IN RURAL AREAS

The project continued the research by analyzing the vulnerability of elderly drivers in rural areas. The objective is to verify that elderly drivers in rural areas are more vulnerable than their younger age counterpart and the urban counterpart, thus requiring specific driver assistance. This section first introduces the method to measure and compare the vulnerability of drivers in different age groups and areas of residency. Then, it summarizes major findings from the comparative study. After that, gaps between elderly drivers' needs and existing driver assistance technologies are discussed.

3.1 The Approach to Assess Driver Vulnerability

3.1.1 Factorization of Contributors to Fatal Crash Density

This study speculates that both aging and rural residency are indicators of drivers' vulnerability. Therefore, it calculates the fatal crash density using the count of drivers involved in fatal crashes per 100 million vehicle-miles traveled (VMT):

$$Fatal\ Crash\ Density\ = \frac{No.\ drivers\ involved\ in\ crashes\ with\ fatal\ injuries}{100\ million\ VMT}. \qquad (1)$$

This density measurement is an indicator of driver vulnerability.

Adopting the approach proposed in Zwerling et al. (2005), this study further define the following measurements:

$$Fatal\ Rate = \frac{No.\ drivers\ involved\ in\ crashes\ with\ fatal\ injuries}{No.\ drivers\ involved\ in\ crashes\ with\ injuries} \qquad (2)$$

$$Injury\ Rate = \frac{No.\ drivers\ involved\ in\ crashes\ with\ injuries}{No.\ drivers\ involved\ in\ crashes} \qquad (3)$$

$$Crash\ Density = \frac{No.\ drivers\ involved\ in\ crashes}{100\ million\ VMT} \qquad (4)$$

Given these defined measurements, the fatal crash density can be decomposed into a product of three contributing factors:

$$Fatal\ Crash\ Density\ (A) = Fatal\ Rate\ (B) \times Injury\ Rate\ (C) \times\ Crash\ Density\ (D) \qquad (5)$$

With the decomposition above, the study can measure the differences between elderly drivers and their younger age and urban residency counterparts from different aspects, helping identify various opportunities for lowering the fatal crash density among elderly drivers in rural areas.

3.1.2 Data Fusion

To calculate the four measurements in Eqs. (1-4), a single data source is not sufficient. As Figure 2 illustrates, the vulnerability study fuses information from three datasets below:

- Fatality Analysis Reporting Systems (FARS): provides information about fatal crashes, as well as drivers involved in these crashes
- Crash Report Sampling System (CRSS): provides information about crashes with various levels of severity, as well as drivers involved in the crashes
- National Household Travel Survey (NHTS): provides VMT

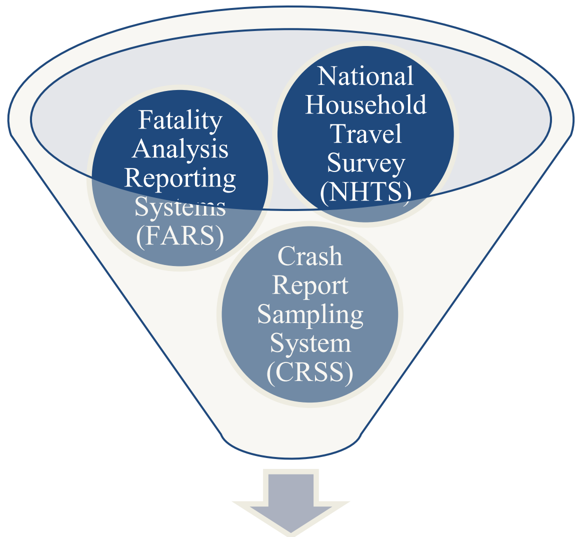

Figure 2. Data sources for measuring fatal crash density and its contributing factors

3.1.3 Measures by Driver Segments

To determine if fatal crash rate and the three contributing factors differ by drivers' ages and areas of residency, the study split drivers into 18 segments that each represents one of the nine age groups and at either rural or urban area.

(1) 0~15 years old
(2) 16~24 years old
(3) 25~34 years old
(4) 35~44 years old
(5) 45~54 years old
(6) 55~64 years old
(7) 65~74 years old
(8) 75~84 years old
(9) 85+ years old

For each driver segment, four quantities need to be measured, as Eqs. (1-5) indicate:

- No. of drivers involved in crashes with fatal injuries
- No. of drivers involved in crashes with injuries
- No. of drivers involved in crashes
- 100 million VMT for each age group in rural and urban areas, respectively

Given these four measurements, the study calculates fatal crash density, fatal rate, injury rate, and crash density for every driver group, as defined in Eqs. (1) and (3~5).

3.1.4 Biases of the Proposed Approach

It should be noted that the proposed approach has two biases:

- Both FARS and CRSS provide the information for calculating "No. drivers involved in crashes with fatal injuries". Measures respectively using these two datasets do not perfectly match but have a slight discrepancy. The vulnerability study chose to use the FARS-based measures.
- The variable "Urban/Rural" in NHTS is about drivers' residency area, whereas in FARS and CRSS it is about the location of crash. The meaning of this variable is not exchangeable across the data sources, and the bias must be noted. However, trips in one's residency area are the majority of all the trips. This study simply treats the location of crash as the residency area of drivers involved in the crash.

3.2 Results and Discussion

The vulnerability study used the data of year 2017 to obtain the measurements. Figure 3 summarizes the result from the data analysis. Major findings are discussed below:

Figure 3. Fatal crash density and the contributing factors by age groups and residency areas

- The fatal crash density quickly increases with age among drivers who are 65 or older. This rate of increase is faster for elderly drivers in rural areas than urban areas.

- The difference of injury rate between drivers in rural and urban areas are almost negligible, except for those who are 85 or older. Specifically, the injury rate noticeably increases with age among drivers who are 85 or older living in rural areas.
- Crash density for elderly drivers (55~84 years old) in rural areas is lower than those in urban area. But this relationship is reversed for drivers who are 85 or older.
- Generally speaking, the fatal rate increases with age, and the rate in rural areas are significantly higher than in urban areas for any age group.

Observations from Figure 3 suggests opportunities for assisting elderly drivers in rural areas:

- The need for assisting elderly drivers is evident by the facts that fatal crash rate, fatal rate, injury rate, and crash density are increasing as drivers become older.
- Elderly drivers in rural areas are vulnerable, manifested by the significantly higher fatal rate among elderly drivers in rural areas than their urban counterpart. The best opportunity to lower the fatal crash density among elderly driver in rural area is to lower their fatal rate. Lowering the injury rate for elderly drivers of 85+ and living in rural areas is also critical.

3.3 Causality and Needs Analysis

Various studies have reported the vulnerability of older drivers on rural roads. Cicchino and McCartt (2015) analyzed the NHTSA's National Motor Vehicle Crash Causation Survey (NMVCCS) dataset and found that driver error is the critical reason for 97% of crashes involving elderly drivers. According to the Human Factors Analysis and Classification System (HFACS) originally developed at the Federal Aviation Administration (Wiegmann and Shappell, 2017), human errors include perceptual errors, decision errors, and skill or performance errors. The NMVCCS survey data shows that inadequate surveillance counts for 33% of errors among elderly drivers, 11% higher than mid-aged drivers. Vision provides 85%~95% of the information necessary for making safe decision in driving. Steplin et al. (1999) stated that drivers who are 65 years old and older experience a variety of limitations on their perception, decision-making and execution. The limitations of visual perception are evident by deteriorated visual acuity, field of view, night vision, depth perception, the ability to change focus, and the ability to adjust to varying illumination. Older drivers also experience slower visual cognition, and they have longer reaction time to stimuli. Their physical vulnerability is another important reason for the increased severity of injuries. These indicate the need for assistance in visual perception and cognition.

Abrams et al. (2022) analyzed rural road fatal crashes using FARS data. The study shows that 84.5% of crash fatalities in rural roads are at non-intersection segments, whereas 68.1% in urban roads. 61% of rural road fatalities happened on less challenging terrains like straight sections of roadway, including two-lane, narrow county roads, and multi-lane interstate highways. Roadway departure and head-on collisions are the most frequent fatal crash types on the rural roads, accounting for 46.4% and 16.5% of total fatal crashes on rural roads. Moreover, 57.6% of roadway departure and 62.9% of head-on collisions that caused fatal crashes are on rural roads. Fatal crashes involving high speeds have also become a concern for rural roads. The statistics indicate the drivers' awareness of the land use, road type and terrain, and their attention to high frequent fatal crashes on particular locations, would help reduce the chance of crashes and lower the severity if a crash cannot be avoided.

3.4 Driver Assistance Technologies

Assisting elderly drivers in visual perception and cognition on rural roads seems critical. The study reviewed the literature on driver assistance technologies to determine if they have met the need of this vulnerable group. Caird (2014) summarizes in-vehicle intelligent transportation systems (ITS) from the view of elderly drivers. Various advanced technologies have been developed to assist drivers in navigation, forward collision avoidance, lane keeping, automated parking, enhanced night vision, and many others. While these technologies seem beneficial to elderly drivers, little is developed to consider their special needs. The technology acceptance level of elderly drivers in rural areas, as well as their abilities to interact with assistive technologies are different than their younger counterpart, and it could be different than their urban counterpart too. A recent study reviewed advanced driver assistance systems (ADASs) that could be helpful for old drivers in perception, planning, and execution (AAA 2021). This report also indicates ADAS can be further customized to meet various needs of elderly drivers.

3.5 Concluding Notes

For elderly drivers who are no longer suitable for driving, automated driving vehicles is a potential solution for maintaining their mobility and safety and reaching out to desired destinations. For those who prefer to drive but with decrements of visual perception, cognition, and execution, ADAS can be customized to assist individuals per their needs. The ultimate goal is to help maintain their independence of life as much as possible by ensuring their safety and mobility in transportation.

4 DRIVING SCENE IDENTIFICATION FOR SITUATIONAL AWARENESS

Our early study based on the FARS dataset and using data mining techniques (Li et al. 2021) indicated that crash risk varies by different driving scene attributes including the driving environment, road infrastructure, location, and others. That study stated that real-time crash risk assessment powered by NHTSA's crash datasets is possible if the attributes characterizing driving scenes can be recognized in real time. Moreover, linking the measure of crash risk to those scene attributes makes the risk assessment transparent. This section summarizes the project's exploration of the visual assistance method for enhancing the situational awareness. Contents of this section was submitted to TRB 2025 Annual Meeting for presentation.

4.1 Background

Recognition of driving scenes from videos and images is a crucial function for automated driving systems (ADS) to learn the interaction between human behaviors and traffic scenarios (Ramanishka et al. 2018). The rapid advancement of autonomous vehicle technology and ADAS necessitates reliable methods for driving scene identification. As these systems become increasingly integrated into modern vehicles, the ability to accurately perceive and interpret complex driving environments is critical to ensuring safety, efficiency, and overall user satisfaction.

Traditional Convolutional Neural Networks (CNN) and novel Transformer models have revolutionized the field of computer vision by demonstrating exceptional performance in visual tasks such as image classification, object detection, and semantic segmentation for driving scene understanding. Driving scene identification provides the information and instructions for the decision-making of autonomous vehicles or ADAS when encountering complicated situations (Muhammad et al. 2022). For example, diverse illumination and weather conditions critically affect the performance of object detection, drivable area segmentation, and lane marking detection for driving scene understanding. Moreover, strategies for ADS such as lane changing, accelerating, and braking need an understanding of specific driving scenarios, such as intersections, road functions, weather-related road conditions, work zones, and so on. In general, effectively and accurately driving scene identification is crucial for ADS and ADAS. This capability helps in making correct decisions, thereby preventing driving accidents (Gupta et al. 2021).

Driving scenes are usually complex, can be classified from multiple dimensions. Therefore, scene identification is a problem of multi-label driving scene classification that characterizes each input data instance using multiple scene attributes (Zhang and Yang 2017). There are two conventional approaches to the multi-label classification. One approach is to train a set of single-task models that each handles the recognition of one attribute. This approach is simple because training individual single-task models for scene classification is relatively straightforward, and handing the issue of data distribution imbalance along one dimension is less challenging. However, the computational cost increases linearly with the number of attributes. The other approach is to train a multitask model where each of the scene attributes is recognized by one dedicated downstream task and all the tasks share the deep feature extractor. Sharing the deep feature extractor can significantly reduce the computational cost compared to the single-task approach in inferences. Directly training such a multitask model requires multi-labeled training data. Unfortunately, in a high-dimensional attribute space, data distribution is highly unbalanced.

(Ding et al. 2020, Zhu et al. 2022). This deficiency of training data has raised an obstacle for following a conventional approach to train a multi-task model.

4.2 Study Contributions

To address the limitations mentioned above, this study is motivated to explore a novel approach to creating a multitask model for the multi-label driving scene classification by leveraging single-task learning. Contributions of this study are twofold:

- A Driving Scene Identification dataset is created, which comprises seven subsets that each provides labels of one specific scene attribute
- The Knowledge Acquisition and Accruing Network framework (KA&AN) is proposed to acquire and accumulate knowledge from single-task learning, addressing the data challenge facing the multi-task learning approach to multi-label scene classification.

The remainder of the paper is organized as follows. Section 4.3 will describe recent studies relevant to this work. Section 4.4 will detail the components of the proposed dataset. The KA&AN framework will be presented in Section 4.5. Section 4.6 will further present the experimental setup and the final classification results. In the end, Section 4.7 will summarize the findings and suggest future research directions.

4.3 Related Work

Recent related work of this study is concentrating on the public driving scene datasets, driving scene classification from a computer vision perspective, and knowledge distillation for knowledge accumulation and rehearsing.

4.3.1 Public Driving Scene Datasets

BDD100K (Yu et al. 2020) is a large-scale driving video dataset provided by the Berkeley DeepDrive (BDD) research group. The image tagging of driving scene attributes contains 6 weather conditions, 6 scene types, and 3 distinct time of the day. For the attribute of scene types, “tunnel”, “residential”, “parking lot”, “city street”, “gas station”, and “highway” are included. Honda HSD (Narayanan et al. 2019) contains 80 hours of diverse, high-resolution driving video data clips collected in the San Francisco Bay Area. Unlike BDD100K, the HSD dataset provides identification of intersection type, overhead structures, and railroads, enhancing the diversity of driving scene categories. ROADWork Data (Admin et al. 2024) is a large-scale public dataset focused on the identification of workzones in 18 U.S. cities. Additionally, it includes fine-grained instance segmentation and semantic segmentation. Other open-source autonomous driving datasets, including Cityspaces Dataset (Cordts et al. 2016), KITTI Dataset (Geiger et al. 2013), and nuScense Dataset (Caesar et al. 2019), are annotated for objective detection, semantic segmentation, and instance segmentation tasks. Through the comparison of these datasets, it is evident that the driving scene identification lacks diversity of image-level annotations in those public datasets.

4.3.2 Driving Scene Classification from Computer Vision Perspective

Most driving scene identification tasks use CNN-based methods. Due to the lack of comprehensively-annotated public driving scene datasets, these tasks typically learn from single-label datasets and limited multi-label ones.

Wu et al. (2021) proposed a deep multi-classifier fusion method base on CNN to recognize 20 classes on an in-house, single-label dataset. Prykhodchenko and Skruch (2022) utilized deep CNN for classifying street-level driving scenes, including urban, rural, and highway. As for multi-task classification, Ni et al. (2022) designed a scene classification deep learning model for identifying the scene using five classes: crosswalk, gas station, parking lot, highway, and street. The classification performance is improved due to several designs of the network. It extracts local features using a fast region-based convolutional neural network (RCNN) with a residual attention block. The network also learns global features using an inception module. Then, both features are fused for scene classification. The study also considers diversity, such as different weather conditions, when collecting data for each class.

A classifier for multi-label road scene classification on the BDD dataset was presented by Duong et al. (2020). Three attributes for scene classification are considered: location, weather, and daytime. The approach in that study enhances the main multi-label classifier with single-label classifiers using a fusing and stacking strategy. Chen et al. (2019) proposed a multi-label neural network for road scene recognition, which incorporates both single- and multi-label classification tasks into a multi-level cost function for training a classifier with imbalanced categories. Additionally, they utilized a deep data integration strategy to improve classification ability. Saffari et al. (2023) identified driving scenes on the HSD dataset using a novel Sparse Adversarial Domain Adaptation (SADA) model to transfer knowledge from the clear weather condition to others such as cloudy, rainy, and snowy conditions.

Current studies have not thoroughly addressed the multi-label driving scene classification problem, mainly due to the lack of open-source large datasets with a comprehensive annotation of road scene attributes and the difficulty in finding effective ways to train networks that can learn from unbalanced data distribution in a high dimensional space of driving scene attributes.

4.3.3 Knowledge Distillation

Knowledge distillation (KD) typically uses a teacher-student model to effectively transfer knowledge from a deep and large model (teacher) to a smaller model (student). Essentially, it is the process of knowledge accumulation and transfer.

The mainstream knowledge distillation methods include response-based KD, feature-based KD, and relation-based KD (Gou et al. 2021). Ma et al. (2023) introduced an innovative knowledge accruing and reusing framework using feature-based knowledge distillation in the medical imaging area. The constructed foundation model addresses the heterogeneous expert annotations in various datasets. To mitigate the forgetting and accrue knowledge, Van de Ven et al. (2020) proposed a brain-inspired method of replay in artificial neural network. Meanwhile, the regulation of hidden layers using feature-based knowledge distillation considers the depth of the teacher model, achieving a higher performance compared to methods that focus solely on the last output layer (Romero et al. 2014).

4.4 The Dataset

Public driving scene datasets often lack diversity and sufficient representation of corner cases from the perspectives of multi-variate scene identification. To address this, the project develops a new dataset called Driving Scene Identification (DSI) dataset, featuring 7 driving scene attributes and

24 labels. The dataset combines images from public sources like BDD100k (Yu et al. 2020), HSD (Narayanan et al. 2019), and ROADWork Data (Admin et al. 2024), along with YouTube footage. Statistics of the dataset are summarized in Table 1

Table 6. Data distribution

	Training	Validation	Testing
Datasets and classes	19,616	8,285	3,934
Weather	2,798	1400	500
clear	653	300	100
overcast	654	300	100
foggy	572	300	100
raining	358	250	100
snowing	561	250	100
Time-of-day	1,656	1,022	300
daytime	734	400	100
dawn/dusk	216	164	100
night	706	458	100
Weather-related road condition	2,295	957	441
dry	811	353	145
snow	936	325	150
wet	548	279	146
Road function	3,891	1,210	639
arterial	1,105	260	100
collector	798	260	100
local	1,038	432	339
interstate	950	258	100
Intersection	1,981	332	367
non	801	147	111
three-way	358	50	91
four-way	673	116	115
roundabout	149	19	50
Workzone	2,121	1,498	662
yes	1,418	964	353
no	703	534	309
Above-road space	4,874	1,866	1,025
open	738	534	309
tunnel	1,136	332	216
over-head bridge	3,000	1,000	500

The identification of "weather" conditions is critical for ADAS and ADS. Extremely adverse weather conditions risk driving safety and the performance of visual tasks; therefore, the identification of weather conditions is indispensable. Our dataset includes 4,698 weather images collected from the BDD100k dataset, encompassing clear, overcast, foggy, rainy, and snowy conditions. Due to the scarcity of foggy scenes, synthetic images were generated to address the issue of unbalanced data in the weather category.

The dataset for classifying "time of day" utilizes the weather dataset because they are both attributes of driving environment. However, the dataset for classifying "time of day" is a subset that contains 2,978 images from the weather dataset. "Time of day" has three classes – daytime, night and dawn/dusk - less than the number of classes for "weather". Therefore, the size of the dataset for classifying "time of day" is reduced to maintain a relatively balanced sample size per class. The classification for "time of day" involves the extraction of abstract features related to the brightness of images. Images captured during night and dawn/dusk exhibit increased noise and lower contrast, resulting in color distortion. Accurately identifying the time of day potentially contribute to reducing biases in image data analysis.

The dataset for classifying "weather-related road condition" contains 3,693 images, collected from a combination of YouTube and BDD100k. Results from this task help adapt the vehicle control and risk perception threshold to adverse road conditions, such as web and snowy surface.

Identification of road function supports route planning and adaptive driving behaviors under different speed limits and complexities of driving scenarios. Notably, there is no systematically annotated public dataset available for the US road functional system. Using the query term "road function" to collect videos from YouTube, frames were sampled by skipping 5 frames to generate the road function dataset. This dataset consists of 5,740 images across 4 classes: arterial, collector, local, and interstate. The local road class includes driving scenes from both urban and rural roads.

Intersections are locations with more conflict points than non-intersection road segments. In urban areas, intersections have various traffic participants and are often equipped with traffic signals or signs. Identifying the intersection type provides the prior knowledge to anticipate potential conflict points and make informed decisions such as yielding, stopping, or merging in complex environments. In rural areas, more fatal crashes occurred at non-intersection road segments. The dataset for identifying intersection types is composed of 2,680 images, categorized into four classes: non-intersection, 3-way, 4-way, and roundabout. Roundabout images are sampled from YouTube videos, and others are sampled from HSD and BDD100k datasets. For example, images of 3-way and 4-way intersections were searched using the query "Entering" from the HSD dataset because this stage provides a better view of intersections than the stage of "approaching" or "leaving" intersections.

Sundharam et al. (2023) developed a dual CNN network to detect workzone scenarios and segment elements that evidence the existence of workzones. Obstacles, such as construction equipment, temporary barriers, and road workers, in the workzone may cause driving safety issues to passing vehicles. Indeed, workzones may require lane closures and detours. By identifying workzones on the road, autonomous vehicles can drive cautiously, such as adjusting the driving lane to avoid crashes there. The training and validation datasets for identifying workzones is mainly sampled from the BDD100k and the HSD dataset datasets, which include 2,382 images. The test dataset consisting of 353 images is sampled from the ROADWork dataset. Images without a workzone were randomly selected from other datasets.

The DSI dataset encompasses a subset of 7,766 images for identifying open roads, tunnels and overhead bridges. This subset is sampled from the HSD dataset using query terms like "over-head bridge" and "tunnel". Images sampled were mainly taken from the view of approaching or entering those structures.

4.5 The Approach

Utilizing the DSI dataset, a learning framework is designed to acquire and accrue the knowledge of identifying multi-variate driving scenes from single-task learning. The learning framework has three components, including the Knowledge Collecting Network, Knowledge Memory Network, and an adaptation module.

4.5.1 Transformer-based Feature Extractor

Swin transformer is a hierarchical transformer. It allows for extracting and capturing both global features and local features, meeting the needs for extracting features for driving scene classification tasks, which are at various scales. Meanwhile, the linear computational complexity in relation to image size brings the flexibility and efficiency, compared with previous proposed transformer model ViT and DeiT (Dosovitskiy et al 2010, Touvron et al. 2021).

4.5.2 Knowledge Acquisition

The core of the Knowledge Collecting Network is centered on the cyclic training of various image classification tasks on the seven subsets of single-labeled images. Sequentially training each individual image classification task aims in acquire the ability to extract features for all tasks on a shared Swin-B backbone. The extracted overall features can be relearned from to support individual classifiers in completing their respective tasks. Unlike single-task classification, this phase acquires knowledge through cyclic training within an epoch, ensuring synchronized learning among the heterogeneous tasks. Yet, incremental learning will cause the catastrophic forgetting and memory conflict during training. Therefore, the Knowledge Memory Network is proposed to address this issue.

4.5.3 Knowledge Accumulation

The Knowledge Memory Network is proposed to accrue and retain learnt knowledge through knowledge distillation. The two-way transfer between KA&AN facilitates continual learning across various tasks and mitigates forgetting due to the jump from one specific task to another. At last, the knowledge will be updated and accrued in the Knowledge Memory Network from regulating each single task in cyclic training.

4.5.4 The Loss Function

The two-way knowledge transfer is a crucial component of the knowledge memory network designed to mitigate forgetting when transitioning from learning one specific task to another. Drawing inspiration from knowledge distillation and teacher-student networks, an inconsistency loss function is introduced to address task variability. This loss is calculated using the Mean Squared Error between the projectors of the teacher (i.e., the Knowledge Memory Network) and student (i.e., the Knowledge Collecting Network) networks. These projectors, derived as linear embeddings from intermediate hidden layers across four stages, have demonstrated better performance compared to using only the final layer (Romero et al. 2014). Subsequently, knowledge accumulation occurs at the end of each training epoch for all tasks. The knowledge memory network is refined using epoch-wise exponential moving average (EMA) (Tarvainen and Valpola 2017), facilitating a gradual transition from the initial learning phase to a memorizing phase. Therefore, the total loss in our framework is the sum of classification loss and the inconsistency loss.

4.5.5 Adaptation for Knowledge Accruing Network

After aggregating information from each individual classification task, a foundation model with generalization is adapted for other tasks in the transportation area. The shared Swin-B backbone possesses the capability to identify not only on each specific single task, but also on the unannotated labels apart from their own task. By finetuning each classifier corresponding to single tasks while keeping the backbone frozen, the challenges posed by heterogeneous label annotations in multi-task learning are addressed.

4.6 Experiments and Results Discussion

To achieve the goal of knowledge acquisition and accruing from multiple single-label classification tasks, an important effort is to evaluate and select the most suitable backbone that delivers the highest performance. Compared with traditional CNN framework, Transformer may achieve higher efficiency and performance doing image classification, objective detection and semantic segmentation tasks in deep learning area. By comparing recent transformer-based state-of-the-art (SOTA) models, Swin-B has been identified as the backbone to be applied within the KA&AN framework. The performance of the KA&AN framework is then verified through ablation studies. Finally, the weights of the trained backbone are loaded, which are further finetuned on driving scene multi-task classification.

4.6.1 Choice for Backbone

Transformer-based backbones can be superior to traditional CNN-based ones, demonstrating robustness and efficiency in classification tasks. Seven driving scene tasks in the dataset are trained and tested on SOTA transformer-based models, including the Swin Transformer and ViT, with varying model sizes and computational complexities. The accuracy (acc) is used as the performance metric, while FLOPs and the number of parameters serve as indicators of model complexity. Table 7 summarizes the comparison results.

Table 7. The comparison of backbones

	Swin-Base	Swin-Small	ViT-Base	ViT-Large
Model Complexity				
FLOPs (G)	15.4	8.7	17.6	76.9
# parameters (M)	88	50	86	307
Accuracy				
Time-of-day	**0.996**	0.913	0.893	0.960
Weather	0.922	0.920	0.909	**0.922**
Weather-related road condition	**0.984**	0.977	0.967	0.966
Road function	**0.998**	0.992	0.954	0.958
Intersection	0.886	0.869	0.934	**0.958**
Workzone	**0.952**	0.879	0.885	0.902
Above-road space	0.946	0.937	0.972	**0.984**
Avg.	**0.955**	0.927	0.934	0.950

In comparing the same model with different weights, the backbones with more parameters and FLOPs perform better than their lighter counterparts. Swin-B outperforms others in five single-tasks for driving scene classification, including time-of-day, weather, road function, weather-related road condition, and workzone, with accuracy improvements of 0.36, 0.01, 0.40, 0.18, and 0.49 over ViT-L, respectively. Although ViT-L's accuracy for identifying intersection type and above-road place are 0.958 and 0.984, respectively, better than Swin-B, the Swin-B is lightweight and more computational efficient. In summary, the Swin-B model is the most suitable choice among the tested backbones, demonstrating an overall high performance and moderate model complexity.

4.6.2 The Foundation Model

Then, the study integrated the Swin-B backbone in the multi-task model and trained it in the cyclically approach as proposed in Section 4.5.2 and 4.5.3. After the training is completed, the Swin-B backbone becomes a foundation model for driving scene identification. Our hypothesis is that the foundation model is comparable to the seven single-task classification models. By further finetuning the classifiers, the final multi-task classification model will perform better than the foundation model. To examine our conjectures, the study compared the classification performance across single-task models, the foundation model, and the final multi-task model, with results summarized in Table 8.

Table 8. Comparison of models

Attributes	Mono-task Models	Foundation Model (AN)	Multi-task Model
Time-of-day	**0.996**	$0.990_{0.006\downarrow}$	$0.990_{0.006\downarrow}$
Weather	**0.922**	$0.918_{0.004\downarrow}$	$0.918_{0.004\downarrow}$
Weather-related road condition	0.984	$0.982_{0.002\downarrow}$	$\mathbf{0.989}_{0.005\uparrow}$
Road function	**0.998**	$0.992_{0.006\downarrow}$	$0.994_{0.004\downarrow}$
Intersection	0.886	$0.883_{0.003\downarrow}$	$\mathbf{0.894}_{0.011\uparrow}$
Workzone	**0.952**	$0.897_{0.055\downarrow}$	$0.903_{0.049\downarrow}$
Above-road space	0.946	$0.950_{0.004\uparrow}$	$\mathbf{0.955}_{0.009\uparrow}$
Avg.	**0.955**	$0.945_{0.010\downarrow}$	$0.949_{0.006\downarrow}$

Table 8 shows that the foundation model is comparable to its mono-task counterparts (with a decrease of accuracy for 1% or less), except in identification of workzone (with a drop of accuracy for 5.5%). After refining the classifiers, the multi-task model's classification accuracy on identifying weather-related road conditions, intersections, and above-road space increments by 0.5%, 1.1% and 0.9% respectively. Compared with mono-task models, the classification performance of time-of-day, weather, and road function dropped slightly, within 0.6%. However, undeniably, there was a relatively severe drop (4.9%) in the accuracy for identifying workzone attribute. The occurrence of a workzone is typically indicated by workzone-related elements such as signs and cones on the road. Traditionally, under the view of computer vision area, it is detected through object detection and segmentation tasks at the pixel level (Sundharam et al. 2023, Shen et al. 2021). Therefore, it is understandable that the performance drop on the workzone task occurs when the overall deep features mix information for multiple tasks at the image level.

To test the performance of the finetuned foundation model for multi-label classification tasks in the real world, this study also randomly annotated small samples with 7 driving scene attributes from the testing dataset. Figure 4 shows a sample of images with the seven attribute values identified by the multi-task classification model. For example, in Figure 4(a), the model identifies that the time of day is daytime with a prediction score of 1.00, the weather is clear with a score of 0.63, and so on. Among the nine examples, four driving scenes are classified accurately with respect to all of the seven attributes. Regarding each of the remaining five examples, the multi-task model successfully identifies the scene with six attributes but had a mistake in one attribute. For example, the multi-task model classifies the road function of the driving scene in Figure 5(e) as a collector, but the true label is an interstate. In Figure 4(i), the four-way intersection is incorrectly classified as a 3-way intersection. Classifying the intersection type from a farther distance is probably a major reason for the mistake.

Overall, the foundation model, after finetuned, has attained a reasonably good ability to identifying driving scenes along the seven attributes, which can replace seven individual models that each is dedicated to one classification task.

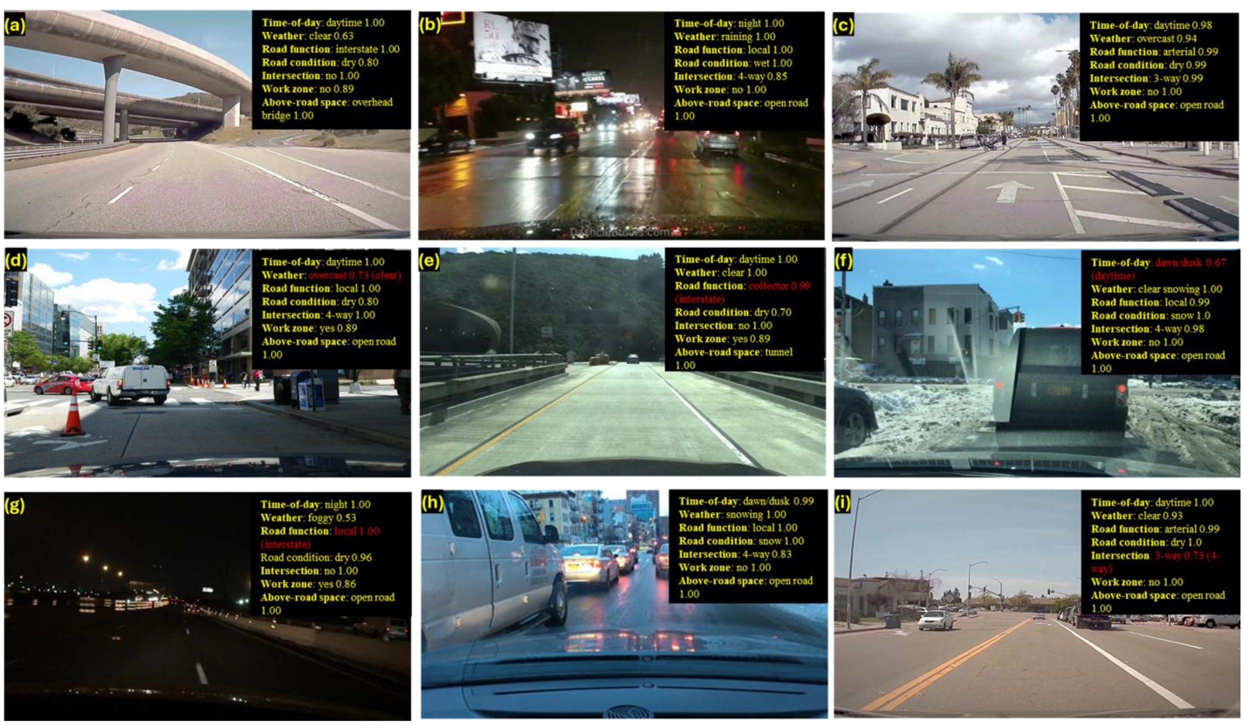

Figure 4. Examples of scene identification results

4.7 Summary

This study developed a driving scene dataset named DSI, which includes well-covered 7 attributes and 24 labels. Utilizing this dataset, the KA&AN deep learning framework is introduced to overcome the difficulty in training a multi-task classification model directly due to unbalanced data distribution on the high-dimension of attribute space for driving scenes. The attained foundation model, after an appropriate finetuning of the classifiers, demonstrates a classification accuracy comparable to what seven individual models can achieve. This exploration verifies our thoughts on addressing data challenges for developing vision assistance to elderly drivers in rural areas where annotated data are not widely available.

The current KA&AN learning framework serves as both a starting point and a foundation for exploring new research directions. For instance, its adaptability to semantic segmentation and instance segmentation needs to be evaluated. Furthermore, exploring the framework's ability to incorporate additional tasks is essential, as new attributes for classifying driving scenes may emerge in the future.

5 CONCLUSIONS

In this project, we explored research questions related to elderly drivers in rural areas through a series of three studies. In the first study, we found that senior residents in rural areas experience decreased accessibility to resources compared to both their younger counterparts and those in urban areas. This issue is particularly notable when accessing healthcare and assisting others with transportation needs. Additionally, seniors in rural areas face reduced mobility, as they heavily rely on automobiles while becoming less capable of driving. Mobility serves as a key moderator of their access to resources, highlighting the critical need for mobility improvements.

There are ongoing debates about the safety of elderly drivers in rural areas. While they have more years of driving experience and face less traffic congestion, aging can lead to declines in perception, cognition, and motor execution. The second study assessed the vulnerability of elderly drivers in rural areas and found that fatal crash density increases with age. Moreover, the fatality rate among elderly drivers in rural areas is significantly higher than in urban areas. The decline in their driving abilities, combined with higher speeds on rural roads, makes them a particularly vulnerable group. Enhancing the safety of elderly drivers in rural areas is critically needed, both by reducing the likelihood of crashes and minimizing fatalities when crashes are unavoidable.

As automobiles remain the primary mode of transportation for seniors in rural areas - likely for at least the next decade - advanced driver assistance for elderly drivers in these regions has become crucial for enhancing both mobility and safety. Among the various opportunities for supporting drivers, the third study of this project focused on improving context-awareness, benefiting both human drivers and autonomous driving vehicles at various levels of automation. Specifically, the study developed a visual intelligent solution that utilizes dashboard cameras as a low-cost, widely deployable sensor, along with a computer vision-based deep learning model to identify driving scenes with seven key attributes. The proposed multi-task classification model effectively addresses the challenge of acquiring annotated and balanced training data. By providing context-awareness, both automated driving systems and advanced driver assistance systems can adjust driving behavior based on specific environments and locations. Human drivers can also receive recommendations to drive cautiously in high-risk scenarios, which can be inferred from the driving scene attributes identified by the proposed model.

The study confirms the demand for safety-enhanced driving assistance among seniors in rural areas. Autonomous driving vehicles with various levels of automation are potential solutions. However, due to the limited availability of annotated data from rural areas, these intelligent vehicles may not perform as well in rural regions as they do in urban areas, where most of the training data for intelligent systems is typically collected. To ensure that driving experiences for seniors in rural areas are as safe and comfortable as those for drivers in urban settings, it is crucial to gather more annotated data - either through real-world collection or computer-generated algorithms. This will help advance solutions for assisting elderly drivers in rural areas.

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