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Driving Performance Indicator (DPI) to Classify Distracted Driving Conditions in the Elderly Females

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Abstract – *The driving performance and distracted driving conditions are among the key elements in road safety assessments. Quantitative measurements were reportedly used to characterize the driving performance. However, the main Driving Performance Indicators (DPI) that evaluate and distinguish the distracted driving conditions are unknown. The present study aimed to select the top three DPIs that best classify three levels of driving distractions targeting the elderly female group based on the publicly available database. Data involved eight driving session records of 15 subjects (female of elderly age group) captured in 62,284 instances x 6 attributes (5 DPI and 1 DriveCondition class) that were extracted based on the inclusion criteria set. The DPI features were selected based on the Correlation-based Feature Selection (CFS) and CorrelationAttributeEval (CA) algorithms of WEKA 3.8, reasoned by DPI's Pearson's correlation results. The Simple Random Undersampling approach was used to resolve the class imbalance state. The 'All' and 'with DPI feature selection DPI' (CFS and CA) datasets were classified using 1NN and J-48 algorithms at 10-fold cross-validation mode into three predefined classes of distracted driving conditions (Relax, Moderate and Intense). Classification accuracies achieved from 'All' and 'with DPI feature selection DPI' (CFS and CA) datasets were 66.10% to 68.86% (1NN) and 68.50% to 71.01% (J-48), respectively. The main DPI subsets nominated by CFS: {Speed, Acceleration, Steering, Laneoffset} and CA: {Speed, LaneOffset, Acceleration} each decreased classification accuracy from All datasets by a minimal 0.4% to 2.8% each. Findings demonstrated that Speed, Acceleration, and Lane Offset were high-ranked DPIs that sufficiently distinguished driving distraction classes for the elderly female drivers.*

Keywords: Classification, distracted driving condition, drive, driving performance, feature selection, elderly female driver

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1.0 INTRODUCTION

Safe driving is known to be governed by various factors such as the gender and age of the driver, driving skills, experiences, driving behavior, driving performance as well as internal and external driving distractions. According to Regev et al. (2018), the driver's gender and age contribute to the risk of fatal injury in potential crashes. The driving skills and experiences are significantly related to driving behaviors (Liu et al., 2020). The internal and external driving distractions, whereas, negatively affect driving performance (Stutts et al., 2003). Of all factors, driving behavior and performance are considered among the most challenging and complex ones to assess.

McLaughlin et al. (2009) defined driver behavior as "tasks or actions, including both driving-related activities as well as non-driving-related activities" while the driver performance was referred to as the "human perceptual and physical capabilities and limitations that affect safe driving". Extensive research works on driver behavior and performance were reported in the past (Qi et al., 2020). The complexity of driver behavior and performance has significantly increased in recent studies when awareness about distracted driving conditions was raised (WHO, 2011). Efforts to identify the underlying causes of distracted driving, relating between distracted driving behaviors, and associating them with crashes or crash risks were reported (Qi et al., 2020). Various quantitative measurements like speed and brake, acceleration, steering angle, lane position, lane offset, lateral acceleration, reaction time, perception, and headway were also used to evaluate driving behavior and performance (McLaughlin, 2009; Papantoniou, 2017).

Statistics have proven that females are considered far safer drivers than males (Åkerstedt & Kecklund, 2001; Kim et al., 2008, Ma & Yan, 2014; Massie et al., 1997; Zhou et al., 2015). Nevertheless, to the best of our knowledge, no study has investigated distracted driving performances with a specific focus on the elderly female group. Also, out of various driving performances measured, it remains uncertain which indicators better evaluate and distinguish distracted driving conditions. Thus, this study was intended to focus on elderly female drivers to select three top-ranked Driving Performance Indicators (DPI) that classify three levels of driving distractions (Relax, Moderate, Intense).

2.0 RELATED WORKS

Past studies emphasized safe driving based on multiple attributing factors from demographic, driving performance, and driving distraction aspects. According to Bucsuházy et al. (2020) and Salmon et al. (2011), human factors are often responsible for the causes of road accidents.

The majority had agreed that gender and age contribute to risky driving behaviors (Bener et al., 2013; Cordellieri et al., 2016; Granié and Papafaya, 2011; Swedler et al., 2012). Statistics have shown that crashes in males were (i) three-fold the women and highest among teenagers (Li et al., 1998), (ii) more than women yearly (NHTSA - Fatality Analysis Reporting System, 2019) (Figure 1), and (iii) more severe than females (Massie et al., 1997). Findings in Bener and Crundall (2008) also proved that there were higher accident rates in males compared to females. A similar effect of more males involved in road fatalities was also evident in Malaysia (Darma, 2017). Li et al. (1998) reported that age-related variation mainly contributes to high crash rates. However, according to them, when age is taken into account, the female is not always safer than the male on the road. Dobson et al. (1999) compared two groups of women drivers aged 18-23 and 45-50 years to study their driving behaviors. They found that mid-aged women are safer drivers compared to the younger ones. Cicchino (2015) extended the comparisons and found that the fatality crash rates declined among the elderly drivers (>75 years old) as compared to the middle-aged group (35-54 years old).

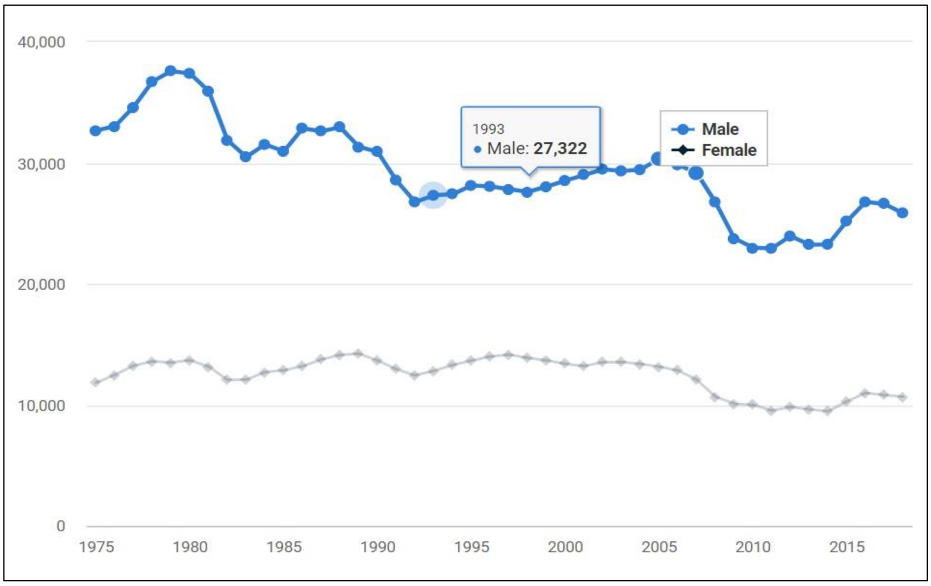

Figure 1: Motor vehicle crash fatalities in the USA by gender in the year 1975-2018 (NHTSA – Fatality Analysis Reporting System, 2019)

Apart from the gender and age factors, the distracted driving condition also poses a threat to road safety issues leading to an increased risk of near-crash or crashes (McEvoy, 2006; Papantoniou et al., 2017). Regan et al. (2008) defined distracted driving as a "diversion of attention from driving towards an object, person, task or an event that is unrelated to driving, which reduces the driver's awareness, ability to control a vehicle, decision making and performance". Among the distraction sources commonly identified were mobile phones, conversation, visuals, music, advertisement signs, and other activities like eating, drinking, or driving under the influence of alcohol (Papantoniou et al., 2017).

Lyon et al. (2020) researched distracted driving by mobile phones and under fatigue. Choudhary et al. (2020) examined the effects of simple and complex conversation texting and complex texting tasks on vehicle-based performance parameters. Maldonado et al. (2020), whereas, stressed the importance of knowing a driver's responses during risky situations to promote safe driving. Aronsson and Bang (2006) analyzed driving behaviors by gender in different designs of urban roads and streets. Their study evident that there was a marginal difference between male and female drivers in terms of speed and headway driving behavior. Variations in speed behavior by gender were also observed in Rohani et al. (2015) when drivers enter the horizontal curves.

Existing works have quantified driving performance by various metrics. Papantoniou et al. (2017) compiled a list of 45 published works concerning driving simulation studies and found that the commonly measured indicators were speed, lane position, reaction time, perception/situation awareness, headway, accident probability, eye glance, acceleration, and deceleration. The distribution of the driving performance measurements reported in Papantoniou et al. (2017) is summarized in Figure 2.

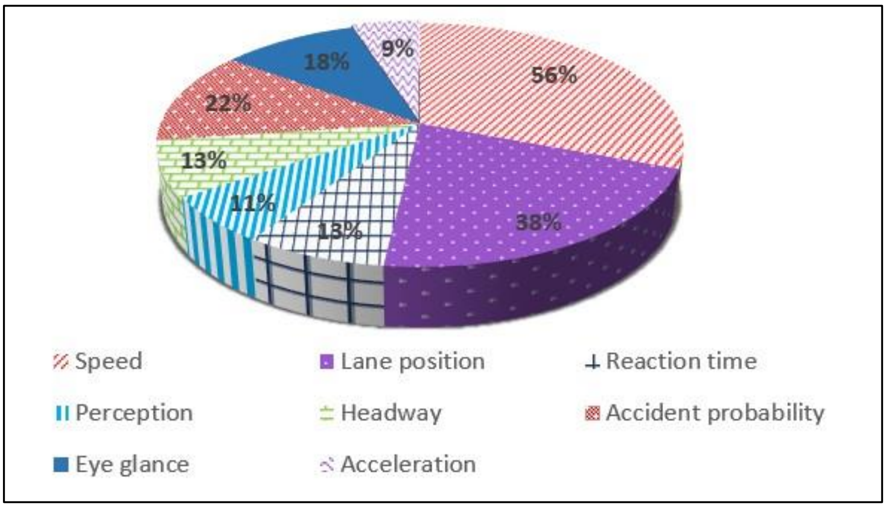

Figure 2: Driving performance measurement focus distribution summarized from 45 papers reviewed by Papantoniou et al. (2017)

Collective findings from the state-of-the-art review summarize that:

i. Female drivers of the middle-aged category are safer on the road;
ii. Driving behaviors are distracted by various internal and external sources; and
iii. Driving performances are measured using various indicators to reflect driving behaviors on the road.

3.0 METHODOLOGY

The entire research framework comprises six main stages: data collection, data extraction and segregation, data pre-processing, 10-fold cross-validation classification, DPI feature selection, and the distracted driving condition classification evaluation (Figure 3).

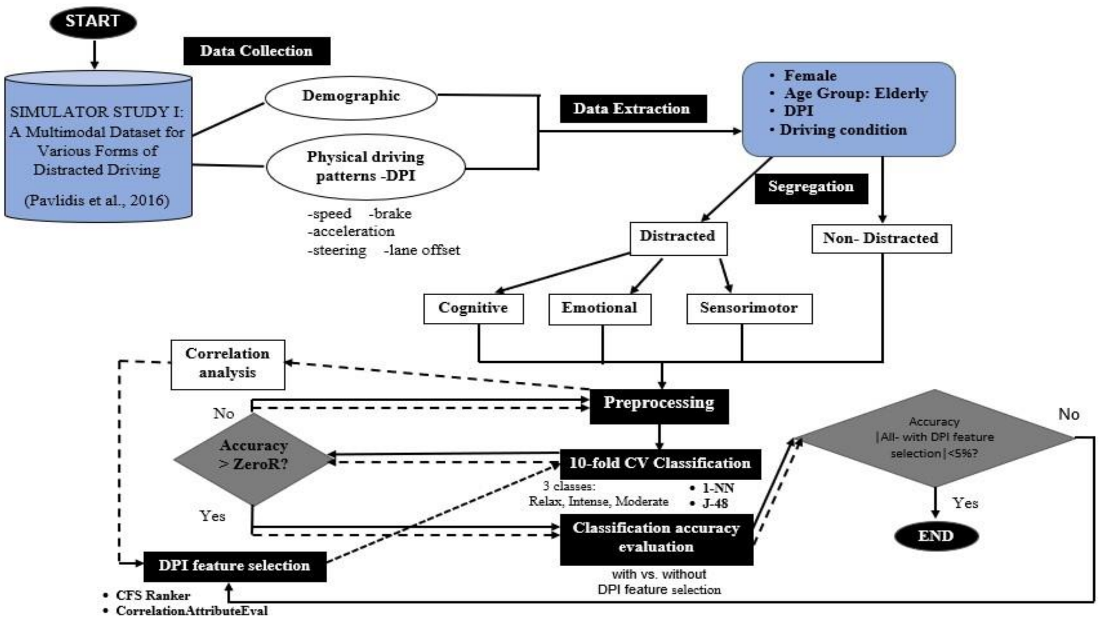

Figure 3: Distracted driving conditions classification based on DPI in elderly females

3.1 Data Collection

The case study involved a multimodal database domain of controlled indoor driving experiments on a driving simulator (manufactured by Realtime Technologies, Inc.) conducted by Pavlidis et al. (2016). The database stores a collection of subjects' eight driving sessions performances on the same highway mode settings under four different conditions: distracted (cognitive, emotional, and sensorimotor distractions) and non-distracted. The subjects belong to licensed drivers with at least 1.5 years of driving experience and of good health condition (clear vision and not under any medication).

3.2 Data Extraction and Segregation

The dataset acquired in the present study was filtered based on the following inclusion and exclusion criteria to accommodate our study scope.

i. *Inclusion criteria*: Female (elderly age group: >60 years old), quantitative driving performance measures: speed, acceleration, brake force, steering, lane offset, and lane position signals.
ii. *Exclusion criteria*: Male or Female (young: 18-27 years old), Male (elderly age group: >60 years old), Female (young age group), physiological signals: perinasal electrodermal activity (EDA), palm EDA, heart rate, breathing rate, and facial expression signals; biographical and psychometric covariates, and eye-tracking data.

Table 1 shows the 66,365 rows x 11 columns layout of the extracted dataset. The rows indicate instances for distracted and non-distraction driving sessions performed by 68 subjects. Meanwhile, the columns represent three nominal (ID, gender, age group) and eight numeric attributes (time, six driving performance indicators, and drive attributes). The study attributes were summarized and described in Table 2.

Table 1: Raw driving performance data captured in Pavlidis et al. (2016) under different driving conditions

ID	Gender	Age Group	Time	Drive	Speed	Acceleration	Brake	Steering	LaneOffset	Lane.Position
T025	F	Elderly	1	1	NA	NA	NA	NA	NA	NA
T025	F	Elderly	2	1	NA	NA	NA	NA	NA	NA
T025	F	Elderly	3	1	NA	NA	NA	NA	NA	NA
:			:	:	:	:	:	:	:	:
:			:	:	:	:	:	:	:	:
T086	F	Elderly	202	8	1.775373	0	34.34601	0.008796	0.112387	5.161617
T086	F	Elderly	203	8	11.88442	0	49.58038	0.008796	0.112387	5.265945
T086	F	Elderly	204	8	49.82024	0	56.17218	0.008796	0.112387	5.265945

3.3 Data Preprocessing

At this level, nine data attributes were screened for irrelevant and redundant information. The ID, Gender, Age group, Time, and Lane Position attributes were filtered. The subjects' identities were unnecessary for the study. The Gender and Age groups were redundant since all data belongs to the same category; female of the elderly age group. Meanwhile, Time was found more informative in its derived quantity "Speed =distance/time" to reflect the subjects' driving performance. The information from Lane.Position, whereas, can be represented by the LaneOffset attribute.

Table 2: Data attribute descriptions

<table>
<tr><th>Attribute</th><th colspan="2">Definition</th></tr>
<tr><td>ID</td><td colspan="2">Subject identification code</td></tr>
<tr><td>Gender</td><td colspan="2">{Male, Female}</td></tr>
<tr><td>Age group</td><td colspan="2">{Young (18-27 years old), Elderly (>60 years old}</td></tr>
<tr><td>Time</td><td colspan="2">Instantaneous measurement in seconds (s) beginning from the driving session.</td></tr>
<tr><td rowspan="5">Drive</td><td colspan="2">8 driving sessions labelled: {1, 2, 3,…,8}</td></tr>
<tr><td>{1} = baseline
• Driving on the simulator after listening to soothing music and sat in a dim-lit room</td><td>{5} = loaded drive
• Driving under challenging conditions (heavy traffic, road construction, traffic delineator posts on two sides).
• Additional cognitive stress included (answering Mathematical questions)</td></tr>
<tr><td>{2} = practice drive
• Familiarization with the simulator drive by changing speed limits throughout sessions
• 80km/h → 50km/h →100km/h</td><td>{6} = loaded drive
• Driving under challenging conditions (heavy traffic, road construction, traffic delineator posts on two sides).
• Additional emotional stress included (answering oral questions)</td></tr>
<tr><td>{3} = relaxing drive
• Driving on a straight section at speed limit 70km/hr
• Twice changing lanes (R→L→R)</td><td>{7} = loaded drive
• Driving under challenging conditions (heavy traffic, road construction, traffic delineator posts on two sides).
• Additional sensorimotor stress included (texting on smartphones)</td></tr>
<tr><td>{4} = loaded drive
• Driving under challenging conditions (heavy traffic, road construction, traffic delineator posts on two sides).
• No additional secondary activity</td><td>{8} = failure drive
• 1st half no distraction
• 2nd half mixed distraction
• Unintended acceleration incident</td></tr>
<tr><td rowspan="6">Driving Performance Indicator (DPI)</td><td>Speed</td><td>Measurement on how fast the car is moving in kilometer per hour (km/h)</td></tr>
<tr><td>Acceleration</td><td>Change of velocity in direction measured in degree (°)</td></tr>
<tr><td>Brake</td><td>A force measured in Newton (N) that slows down the car when the brake pedal is pressed.</td></tr>
<tr><td>Steering</td><td>Angle between the front of the vehicle and the steered wheel direction measured in radian (rad).</td></tr>
<tr><td>LaneOffset</td><td>Car position either to the right (+ve offset) or left (-ve offset) from the lane centerline.</td></tr>
<tr><td>Lane.Position</td><td>Car position either at center, on the right, or left of a lane, measured by distance (in meter) between the center of the car and the center of the driving lane (m).</td></tr>
</table>

The Drive attribute was labeled from 1 to 8 driving sessions indicating the driving conditions imposed on the subjects during each driving session (Table 2). The Drive sessions were taken as the nominal DriveCondition class attributes, predefined as Practice (Drive = {1,2}), Relax (Drive = {3}), Moderate (Drive = {4, 5, 6, 7}), and Intense (Drive = {8}). The DriveCondition classes reflect different intensity levels of driving distractions. However, the Practice class was filtered at the data preprocessing level since the Drive = {1,2} were intended for the subjects to familiarize themselves with the simulator and thus do not belong to any distracted driving conditions.

3.4 DPI Feature Selection

Preprocessed data were subjected to Pearson's correlation analysis between the DPI attributes (speed, acceleration, brake, steering, lane offset). Following the conventional Guilford Rule of Thumb, r = ±0.4 indicates a moderate correlation (Schober et al., 2018). Therefore, the correlation value between two DPI attributes of at least ±0.4 was considered sufficient to represent one another.

The Correlation-based Feature Selection (CFS) and CorrelationAttributeEval (CA) algorithms in WEKA 3.8 were used to evaluate and select important DPI attributes that contribute most to distinguish distracted driving classes. CFS ranks the DPI attributes according to their correlation with the class attribute (DriveCondition) in descending order. DPI attributes that indicate a high correlation with the class label will be ranked at a higher priority. Meanwhile, CA returns rankings based on Pearson's correlation between the DPI attributes and the class attribute. Sets of high-ranked DPI attributes were selected via the findings from (i) CFS and (ii) CA justified with Pearson's correlation values between the DPI attributes.

3.5 Distracted Driving Condition Classification

At this level, there were three datasets derived from Data Preprocessing (All and 'with DPI feature selection DPI' (CFS and CA)). The former accounts for five DPI attributes (speed, acceleration, brake force, steering, lane offset) while the latter considers the top three featured DPI attributes. A potential class imbalance state was investigated. This state occurs when at least a class in the dataset having a smaller number of samples (instances) compared to the others. In order to avoid classification biased towards the majority class, the distributions of distracted driving condition classes (Relax, Moderate, Intense) were evaluated by the number of instance counts. The class imbalanced state was resolved using a Simple Random Undersampling approach on the majority class.

The datasets will be classified on 10-fold cross-validation mode into the three predefined classes using 1-NN and J-48 algorithms of WEKA 3.8. The findings were presented on confusion matrix mappings and evaluated by the percentage of correctly classified instances into three distracted driving conditions (Relax, Moderate, Intense). The ZeroR algorithm was used as the standard baseline for the classification accuracy benchmark. Distracted driving conditions classified at accuracies above ZeroR baseline were deemed reliable. Classification performances on DPI-selected datasets (CFS and CA) were compared with All (no DPI selection) at a minimal margin difference set at 5% (Equation (1)). The DPI attributes identified from CFS and CA selections that return classification accuracies within the marginal difference were determined as the main DPI indicators.

$$|All - selected\ DPI|\ accuracy\ \% \leq 5\% \quad (1)$$

4.0 RESULTS AND DISCUSSION

Figure 4(a) shows the distracted driving condition distributions for the preprocessed data; consisting of 15 subjects (female of elderly age group) recorded in 62,284 instances and six attributes (5 DPI and 1 DriveCondition class attribute). The phenomenon of class imbalance was observed whereby most instances (44,299) were biased towards the Moderate class while the least instances (3,274) belong to Intense. Data preprocessing and Simple Random Undersampling approach resulted in a balanced count of 3,274 instances each for the three DriveCondition classes (Moderate, Relax, and Intense) as shown in Figure 4(b).

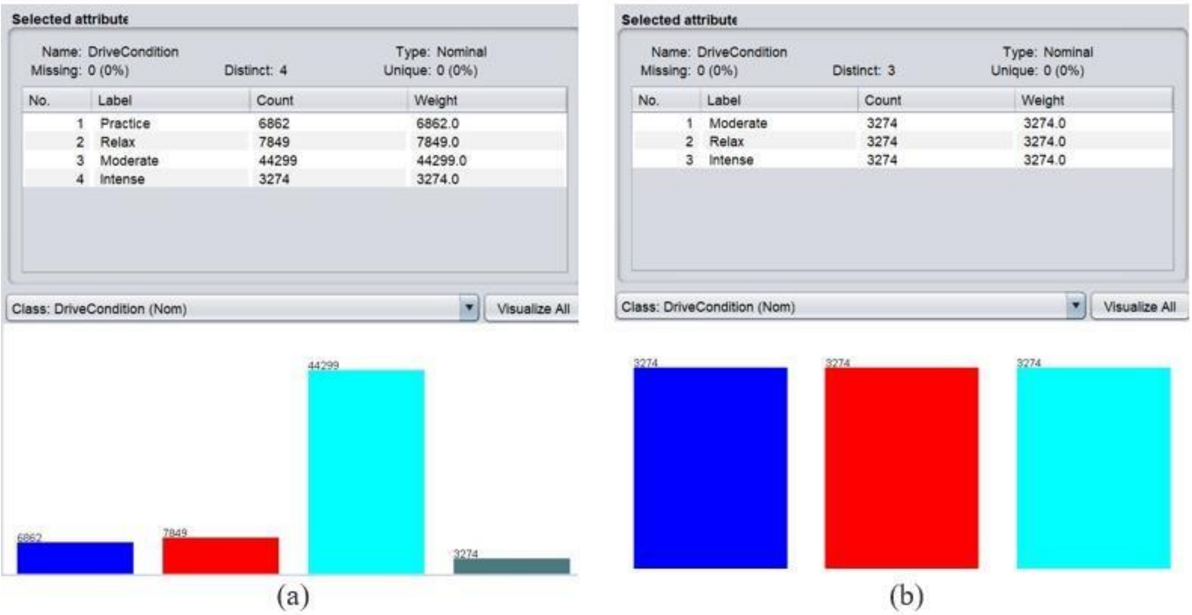

Figure 4: DriveCondition classes distribution visualized in WEKA (a) before and (b) after data pre-processing and Simple Random Undersampling approach

Pearson's correlation analysis examined between two DPI attributes (speed, acceleration, brake force, steering, lane offset) of the preprocessed data is shown in Table 3. All DPI shows negligible correlation except for the Brake vs. Speed and Brake vs. Acceleration showing moderate correlation level. This observation indicates that two DPI attributes ({Brake, Speed} and {Brake, Acceleration}) were related to one another at a moderate level. This finding was in agreement with de Groot et al. (2011) findings that the braking maneuver was characterized by the speed at brake onset.

Figures 5 and 6 show the DPI attributes selected from CFS and CA approaches respectively. Findings show that CFS selected four main DPI attributes in descending ranking {Speed, Acceleration, Steering, Laneoffset}. Meanwhile, CA ranked five DPI attributes by its correlation strength with the DriveCondition class in descending priority order of {Speed, LaneOffset, Brake, Acceleration, Steering}.

CFS results showed the Brake was a less important feature. CA ranked the Brake indicator third. However, Pearson's correlation in Table 3 proved that Brake vs. either Speed or Acceleration returned moderate correlation results. Meaning that at a moderate level, the Speed or Acceleration could represent the Brake information. Therefore, Acceleration, which was ranked second in CFS, was used to represent the Brake indicator. The resultant top three main DPI features from CA were decided to be {Speed, LaneOffset, Acceleration}.

Table 3: Pearson's correlation value between two DPI

	Speed	Acceleration	Brake	Steering	LaneOffset
Speed	1				
Acceleration	0.179106	1			
Brake	-0.451400*	-0.422340*	1		
Steering	-0.029530	-0.005540	-0.002100	1	
LaneOffset	-0.032600	0.028040	-0.026610	-0.099710	1

$0.4 \leq r^{*} \leq 0.59$ (moderate correlation)

The effects of the selected DPI attributes to distinguish DriveCondition classes were evaluated in classification analysis benchmarked on the ZeroR algorithm. The results are depicted in Figure 7. Classification accuracies were compared across three datasets (All and 'with DPI feature selection DPI' (CFS and CA)) and summarized in Table 4. The classification accuracies obtained ranged from 66.10% to 71.0% and passed the ZeroR benchmark at 33.29%. J-48 algorithm returned higher classification accuracies by 2.15%-2.82% than that of 1-NN in three datasets. However, the dataset with selected DPI attributes resulted in a gradual decrement of classification accuracy; All → CFS → CA by 0.40% and 2.20% on J-48 and 0.98% and 1.78% on 1-NN. The difference was merely within the minimal preset 5% margin difference from All dataset.

```
=== Attribute Selection on all input data ===

Search Method:
        Greedy Stepwise (forwards).
        Start set: no attributes
        Merit of best subset found:    0.121

Attribute Subset Evaluator (supervised, Class (nominal): 6 DriveCondition):
        CFS Subset Evaluator
        Including locally predictive attributes

Selected attributes: 1,2,4,5 : 4
                     Speed
                     Acceleration
                     Steering
                     LaneOffset
```

Figure 5: Four selected DPI attributes from Correlation-based Feature Selection (CFS)

```
=== Attribute Selection on all input data ===

Search Method:
        Attribute ranking.

Attribute Evaluator (supervised, Class (nominal): 6 DriveCondition):
        Correlation Ranking Filter
Ranked attributes:
 0.1869   1 Speed
 0.1223   5 LaneOffset
 0.0865   3 Brake
 0.0276   2 Acceleration
 0.0117   4 Steering

Selected attributes: 1,5,3,2,4 : 5
```

Figure 6: Five DPI attribute rankings from CorrelationAttributeEval (CA)

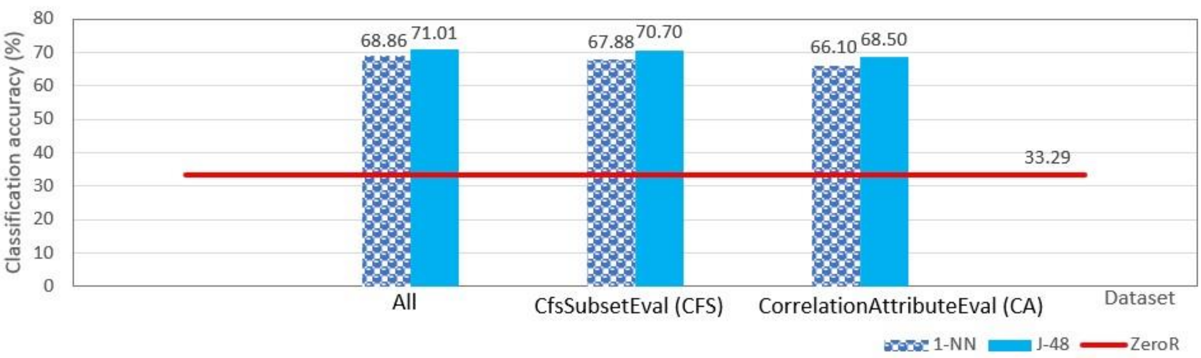

Figure 7: Percentage accuracies of the distracted driving condition classifications for All and 'with DPI feature selection (CFS and CA)' using the 1-NN and J-48 algorithms

Table 4: DPI attributes involved in All and 'with DPI feature selection (CFS and CA)' dataset

All	CFS	CA
• Speed • Acceleration • Brake • Steering • Lane Offset	• Speed • Acceleration • Steering • Lane Offset	• Speed • Acceleration • Lane Offset

At this stage, it was confirmed that Speed, Acceleration, and Lane Offset determined from CA were the top three key DPI to classify the distracted driving conditions. Figure 7 was detailed in Figure 8 in confusion matrix forms indicating the number of instance count classified into their respective classes. Numbers displayed at the matrix diagonals of Figure 8 were the correctly classified instances while the remaining were the misclassified ones. Findings show that there were more misclassifications between Relax-Intense classes (563 to 728 instances wrongly classified) as compared to misclassifications between Moderate-Intense (312 to 475 instances wrongly classified) and Moderate-Relax (402 to 549 instances wrongly classified).

a	b	c	<-- classified as
2406	495	373	a = Moderate
502	2181	591	b = Relax
441	657	2176	c = Intense

All

a	b	c	<-- classified as
2320	515	439	a = Moderate
549	2040	685	b = Relax
457	683	2134	c = Intense

CA

(a)

a	b	c	<-- classified as
2434	402	438	a = Moderate
474	2237	563	b = Relax
361	609	2304	c = Intense

All

a	b	c	<-- classified as
2337	462	475	a = Moderate
453	2158	663	b = Relax
312	728	2234	c = Intense

CA

(b)

Figure 8: Confusion matrix of distracted driving condition classifications for All and CA datasets using (a)1-NN and (b)J-48

5.0 CONCLUSION

Five quantitative DPI (speed, acceleration, brake force, steering, and lane offset) were assessed from a public driving simulator database. These indicators were used to distinguish three classes of distracted driving conditions (Relax, Moderate, and Intense) of the elderly females. DPI feature selection was performed using CFS and CA algorithms to determine the key indicators that correctly classify distracted driving conditions. The classification performances for All, CFS, and CA datasets were examined on 1-NN and J-48 algorithms showing accuracy achievements between 66.10% to 68.86% and 68.50% to 71.01% respectively. Classifying the selected DPI from CFS and CA reduces the accuracies by 0.4% to 2.8% which is considered acceptable (within 5% marginal difference). Conclusively, three key DPI attributes that distinguish distracted driving conditions were Speed, Acceleration, and Lane Offset. Findings from the present study can be extended into DPI consistency evaluation by the individual subject to enhance the classification accuracy.

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