Received January 3, 2021, accepted January 27, 2021, date of publication February 1, 2021, date of current version February 8, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3055870

Driving-PASS: A Driving Performance Assessment System for Stroke Drivers Using Deep Features

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This work was supported in part by the Institute for Information and Communications Technology Promotion (IITP) Grant funded by the Korean Government (MSIP) (Resilient Cyber-Physical Systems Research) under Grant B0101-15-0557, in part by the DGIST Research Program of the Ministry of Science, ICT and Future Planning (MSIP) under Project 21-BT-05, in part by the Transportation and Logistics Research and Development Program funded by Ministry of Land, Infrastructure and Transport of Korean Government under Grant 20TLRP-B131486-04, in part by the National Research Foundation of Korea Grant funded by the Government of Korea (Ministry of Science and ICT) under Grant NRF-2018R1C1B5043803, in part by the Institute of Information and Communications Technology Planning and Evaluation (IITP) Grant funded by the Korean Government (MSIT) (Artificial Intelligence Graduate School Program (Hanyang University)) under Grant 2020-0-01373, and in part by the research fund of Hanyang University under Grant HY-202000000700016.

ABSTRACT Despite any doubts about driving safety, many stroke drivers drive again due to the absence of valid screening tools. The on-road test is considered a formal assessment, but there are safety issues in testing directly on stroke patients who are not fully capable of driving. A driving simulator is a promising tool since it provides meaningful information for identifying hazards to driving safety across different driver populations and driving conditions. Using the advantages of a driving simulator, we propose a Driving Performance Assessment System for Stroke drivers (Driving-PASS). Driving-PASS is designed not only to pre-screen invalid stroke drivers before the on-road test but also to provide problematic driving items for the use in driving rehabilitation. To design assessment classifiers, i.e., the core engine of Driving-PASS, we collect driving data from a total of twenty-seven participants in thirteen driving scenarios. Thereafter, we get subjective assessment results from ten driving evaluators in eleven assessment items. By using driving data and subjective assessment results, we construct eleven assessment classifiers for ten driving ability items and one driving suitability item. We addressed the technical challenges such as handcrafted features and imbalanced dataset by a feature extraction method using pre-trained CNN models and a resampling method. Through comprehensive performance evaluation, we build eleven accurate assessment classifiers in Driving-PASS by carefully selecting deep features in each assessment item. We envision that Driving-PASS can be used as a pre-screening tool for evaluating stroke drivers and will ultimately improve road safety.

INDEX TERMS Driving assessment, driving performance, stroke drivers, deep features.

I. INTRODUCTION

Driving is a complex task that requires many skills, such as cognitive and perceptual-motor behaviors [1]. While the ability to drive anywhere, anytime, is one of the essential forms of independence, driving ability for stroke survivors is affected in various ways, including physical effects, visual problems, cognitive effects, fatigue, and epilepsy [2].

Stroke patients were not different from healthy people in simple driving tasks, but deficits became apparent in complex tasks, causing many driving errors [3]. Nevertheless, many stroke survivors return to driving. In the Republic of Korea, 66.1% of patients with first-ever stroke return to driving at a mean of 2.15 months after stroke [4]. It is essential to decide the returning time for stroke survivors since they are all different in the severity of residual symptoms and the degree of recovery. If driving is not appropriate, proper driving rehabilitation is required until recovery.

The associate editor coordinating the review of this manuscript and approving it for publication was Juan Wang.

Guidelines for stroke drivers vary from country to country. Durations of driving cessation after stroke range from one to six months, depending on the country: one month in New Zealand [5], one month in French [6], three to six months in the United States [7], and six months in Belgium [8]. In general, most driving guidelines for stroke patients recommend stopping driving for at least one month after a stroke [9].

After the driving cessation, stroke drivers undergo a comprehensive evaluation of driving abilities (e.g., clinical off-road tests and an on-road test) to identify potential sequelae and assess driving suitability. Due to limited financial and human resources [10], choosing a reliable and valid instrument remains a critical concern in making decisions about the withdrawal of the driving license, its retention, or its restriction [11]. Stroke survivors do not need to notify the driver licensing authority [12] if there are no residual neurological deficits (visual field defects, cognitive defects, and impaired limb function) in the comprehensive evaluation after one month [13]. However, if there are residual neurological deficits, the patient is responsible for reporting to the driver licensing authority [14]. Physicians who take care of stroke patients also have an ethical duty to notify the driving licensing authority [15].

Despite clear guidelines for returning to driving after a stroke, there are remarkable differences between restrictions and compliance [16], [17]. Surprisingly, many stroke survivors resume driving without medical clearance due to the absence of valid screening tools. In the United States, 30% to 43% of the approximately 6 million stroke survivors drive again within a year, and 87% of them return to driving without formal driving evaluation [18]. Furthermore, a relatively small percentage of stroke survivors (25.9%) received driving evaluations or advice before return to driving in the Republic of Korea [19]. Also, stroke patients themselves and their families tend to overestimate the driving performance of stroke survivors [20]. This improper care of stroke survivors increases the risk on the road, and actual car accidents by stroke survivors have been reported [21].

For evaluating the driving performance of stroke drivers, three types of assessment methods have been developed: an off-road test, an on-road test, and a driving simulator test.

First, the off-road test assesses three main functions relevant to driving for medical clearance: motor, visual, and cognitive functions [22]. The motor function is evaluated by muscle testing, such as range of motion and grip strength. Useful Field Of View (UFOV) [23] is widely used for assessing the visual function. To assess the cognitive function, many off-road tests such as a paper and pencil tests or a computer-based psychometric tests have been developed, e.g., Motor-Free Visual Perceptual Task (MVPT) [24], Trail Making Test (TMT) [25], Cognitive Behavioral Driver's Inventory (CBDI) [26], Sensory-Motor and Cognitive Test (SMCTest) [27], and Stroke Driver Screening Assessment (SDSA) [28]. However, the off-road test has limitations in recognizing subtle motor, cognitive, and visual deficits because these deficits become apparent in highly demanding driving situations [29].

Second, the on-road test, a.k.a. a behind the wheel test, is considered as the gold standard for assessing driving performance [30]. On-road test, administered by the motor vehicle licensing authority, helps to assess functional capability to drive. However, this test cannot evaluate complex and potentially dangerous driving situations (e.g., collision avoidance) [31]. There are limitations to testing for all stroke survivors, such as safety concerns and resource limitations.

Third, driving skills are a complex combination of visual, cognitive, and physical functions and cannot be evaluated separately, so driving simulators are a promising tool for evaluating overall driving skills. The driving simulator is practical, safe, cost- and time-effective due to controllable and repeatable driving test environments [32]. In addition, a cognitive function test in challenging driving scenarios and analysis with standardization are possible [33]. Nevertheless, there is no standard evaluation protocol because there are many degrees of freedom in creating a driving environment and using driving profile data.

To safely and accurately assess stroke drivers' driving performance, we propose a Driving Performance Assessment System for Stroke drivers (Driving-PASS) based on a driving simulator. The proposed system is designed to pre-screen invalid stroke drivers before the on-road test and provide problematic driving items for use in driving rehabilitation.

The major contributions of this paper are as follows:

- We propose a driving performance assessment system that pre-screens invalid stroke drivers in an on-road driving test and provides problematic driving items for driving rehabilitation, called Driving-PASS.
- In Driving-PASS, technical challenges lie in limitations of handcrafted feature design and imbalanced dataset problems. We propose a feature extraction method using pre-trained CNN models and a resampling method to compensate for the challenges.
- By carefully selecting deep features and using a resampling method in each item, we build accurate eleven assessment classifiers, the core engine of Driving-PASS. We expect Driving-PASS to be an effective pre-screening tool to improve the safety of stroke drivers.

The rest of the paper is organized as follows. Section II introduces driving simulator-based assessment methods in related work. In section III, we propose eleven assessment classifiers of Driving-PASS to identify problematic driving abilities and judge driving suitability. Section IV evaluates the classification performance of the classifiers. Section V discusses the limitations of this work and future work. Finally, this paper concludes in Section VI.

II. RELATED WORK

In this section, we conduct a literature review on assessing driving performance based on a driving simulator. Table 1 shows the summary of relevant studies, taking into account

TABLE 1. Driving simulator study for measuring driving performance.

Num.	Category	Subcategory	Performance Measurement	Analysis	Participant
1.	Objective	Var.	3 measurements: Standard deviation of lateral position and Standard deviation of mean speed in straight and curvy road	ANOVA analysis	16 healthy participants remained awake overnight [34]
2.	Objective	Err.	Number of accident, 8 driving faults (e.g., Driving with headlights switched off at nighttime, Disregarding the speed limit)	T-test	Patients suffering from the relapsing-remitting form of multiple sclerosis [35]
3.	Objective	Err.	Number of collisions in 14 scenarios	χ^2 test and Fisher's exact test	36 patients with advanced glaucoma and 36 age-matched healthy people [36]
4.	Objective	Var. & Err.	12 measurements (e.g., Standard deviation of steering wheel rotation, Number of times car travels off road)	T-test and logistic regression	29 Alzheimer disease patients and 21 Control participants [37]
5.	Objective	Var. & Err.	14 measurements (Capture four primary skills: braking, speed control, steering, and judgement. e.g., rolling stops, deceleration smoothness, collisions)	ANOVA	13 Autism spectrum disorder patients and 26 Control participants [38]
6.	Objective	Var. & Err.	11 measurements (e.g., Speed, Lane, Center, Stop Sign)	Discrimination and Pearson correlation	17 head-injured and 148 uninjured adults [39]
7.	Objective	Var. & Err.	5 measurments: Road position, Speed, Speed deviation, Reaction time, Crashes	T-test	18 patients with untreated major depressive disorder and 29 healthy people [40]
8.	Objective	Var. & Err.	10 measurements (e.g., Mean speed, Brake pedal pressure, Number of lane boundary crossings)	T-test	8 subjects with suspected dementia and 14 healthy people [41]
9.	Objective	Var. & Err.	5 measurements (e.g., total run length, speed violation) and 4 operational parameters (e.g., Curvature error, Steering wheel rate)	Multivariate analysis of variance	Senior drivers and advanced age senior drivers (total 53 volunteer older adults) [42]
10.	Objective	Var. & Err.	5 measurements: Maximum velocity, Mean velocity, Lane position, Reaction time, and Collision	T-test and Pearson's chi-squared test	20 adults with attention deficit-hyperactivity disorder(ADHD) and 21 controls without ADHD [43]
11.	Objective	Var. & Err.	6 measurements (e.g., Top speed, Mean speed, Lane accuracy) and 6 errors (e.g., Accident, Ignore speed limit, Crossing safety line)	Cronbach's alpha analysis	49 older drivers in on-road test and driving simulator assessment [44]
12.	Objective	Var. & Err.	12 measures in two categories (Speed control and Direction control): e.g., Speed, Speed variability, Lane position error, Collisions driving parameters	T-test	17 patients with whiplash associated disorders (WAD) and 26 healthy people [45]
13.	Objective	Var. & Err.	3 measurements by a weighted sum of the z-transformed values: SpeedScore, Violoation-Score, SteeringErrorScore	Pearson intercorrelation	804 learner drivers in simulator test and on-road driving test [46]
14.	Subjective	Rating	14 rating items in four broad domains (Handling of Controls, Regulation of Trajectory, Basic Maneuvers, and Higher-order Skills)	T-test	11 patients with traumatic brain injury (TBI) and 16 healthy people [47]
15.	Subjective	Rating	20 rating items (e.g., Steering, Changing gears, Using pedals, Attention to left)	Rasch analysis	31 Stroke patients [48]

Num.: Number, Var.: Variables, and Err.: Errors

performance measures. We note that driving performance takes into account two aspects: driving abilities and driving suitability.

For driving abilities, we need to consider the design of assessment items. The items are divided into two categories: *objective* and *subjective*. These *objective* and *subjective* items are primarily designed to evaluate driving abilities, such as speed, steering, road traffic compliance, and emergency response. The researcher variously organizes individual items according to the research purpose. *Objective* item consists of performance measurements, such as statistical variables (e.g., standard deviation lateral position) [34], and driving errors (e.g., number of collisions) [36]. These measurements are sometimes used individually, but in most cases, they are used together, depending on research purposes [37]–[46]. On the other hand, *subjective* item consists of performance measures such as the Likert-scale score and binary decisions (e.g., Pass or Fail). The measurements are graded based on the subjective judgments [47] or pre-defined criterion [48] using the driving evaluator's observations of driving patterns on the specific driving scenarios.

These *objective* and *subjective* items are mainly used for factor analysis by comparing two groups (patients vs. healthy people) or two different situations (driving simulator vs. on-road driving). Both items have the following advantages and disadvantages: *Objective item* is reliable and produces many objective measurements from a driving simulator. However, due to the high degree of freedom to create driving features in the driving simulator, it is challenging to select optimal features, i.e., limitations of handcrafted feature design. *Subjective* items consist of categorical variables (e.g., Likert-scale) and intuitively easy to understand the relative driving performance. However, there are reliability issues due to the way the human raters evaluate it. In addition, the subjective assessment using these items is time-consuming and expensive if many evaluators are required.

For the driving suitability, it is essential to evaluate the driving abilities comprehensively and to establish pass or fail criteria. Driving suitability is determined by considering the evaluation results of overall driving abilities. The evaluation results of driving abilities are converted to a single score by using functions such as z-score or sum [49]. The final driving suitability is then determined by considering the distribution of the control group [47], results of driving evaluators [50], or results of the on-road test [51]. In this work, we use the results from driving evaluators as the criteria for determining driving suitability.

Note that we use two *objective* and *subjective* data in our system for constructing assessment classifiers with an Artificial Intelligence (AI) approach. The *objective* data and *subjective* data are used for the classifiers as input data and label data, respectively.

Research related to the evaluation of driving performance in stroke drivers is well studied. However, to the best of our knowledge, automated studies using AI is rare. This may be due to difficulties collecting data from stroke patients and evaluating various traffic situations from different driving simulators. In this work, we design the subjective assessment and automate the manual assessment task with AI techniques.

There are four categories of automation methods using artificial intelligence (AI) techniques, i.e., machine learning and deep learning, as shown in Fig. 1. The traditional machine learning approach consists of four processes [52]: Input, Feature extraction, Machine learning for Classification, and Output, as shown in Fig. 1-(a). This approach requires the feature extraction process for generating handcrafted features before a machine learning task. The limitations of this approach are highly susceptible to errors and only suitable only one domain [53]. With advances in deep learning technology,

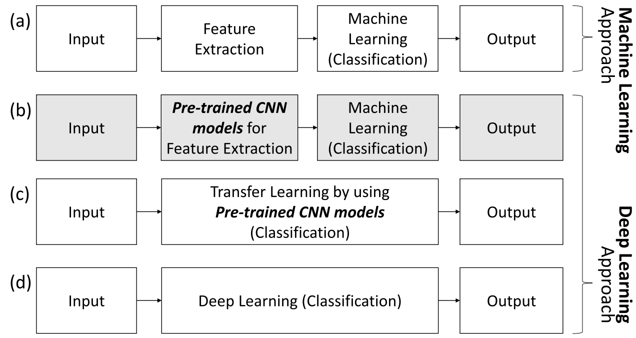

FIGURE 1. Classification approaches by using machine learning and deep learning.

deep learning has been widely used in many applications such as automobile [54], sports [55], and healthcare [56]. The three main approaches to using deep learning techniques depend on the data size and the research purpose. Fig. 1-(b) is to replace the ML approach's feature extraction component with pre-trained CNN models' deep features [57], [58]. This approach is effective for developing AI models using relatively small data sets without any specific domain knowledge. Fig. 1-(c) shows transfer learning, which is one of the deep learning techniques [59]. Transfer learning is to take a network that is well trained in one domain and adapt it to a new task in a different domain, reducing the time to develop deep learning models. Fig. 1-(d) shows a conventional deep learning approach. The structural characteristic is end-to-end learning. While designing and optimizing a deep learning model takes a lot of time and trial and error, this approach is the best of the three deep learning approaches.

Among these approaches, we choose a deep learning approach using deep features of pre-trained CNN models, as shown in Fig. 1-(b). With a small data set, it can effectively perform the classification tasks using deep features without manual feature extraction. In particular, the proposed Driving-PASS uses deep features to compensate for the limitations of hand-crafted feature design in various driving scenarios.

Our previous work [60] used a conventional machine learning approach, as shown in Fig. 1-(a). The differences compared to the previous work are as the following: First, we recruit additional evaluators (a total of ten driving evaluators) to improve the reliability of the subjective assessment. Second, we complement additional technical methods in the system's functional components, i.e., Feature engineering, Resampling, Automated Machine Learning (Auto-ML), to enhance the performance of Driving-PASS.

III. PROPOSED METHOD

In this section, we introduce the detailed process of Driving-PASS. Driving-PASS consists of three processes, as shown in Fig. 2: driving test, subjective assessment, and classification. Driving-PASS is aiming at providing insufficient driving

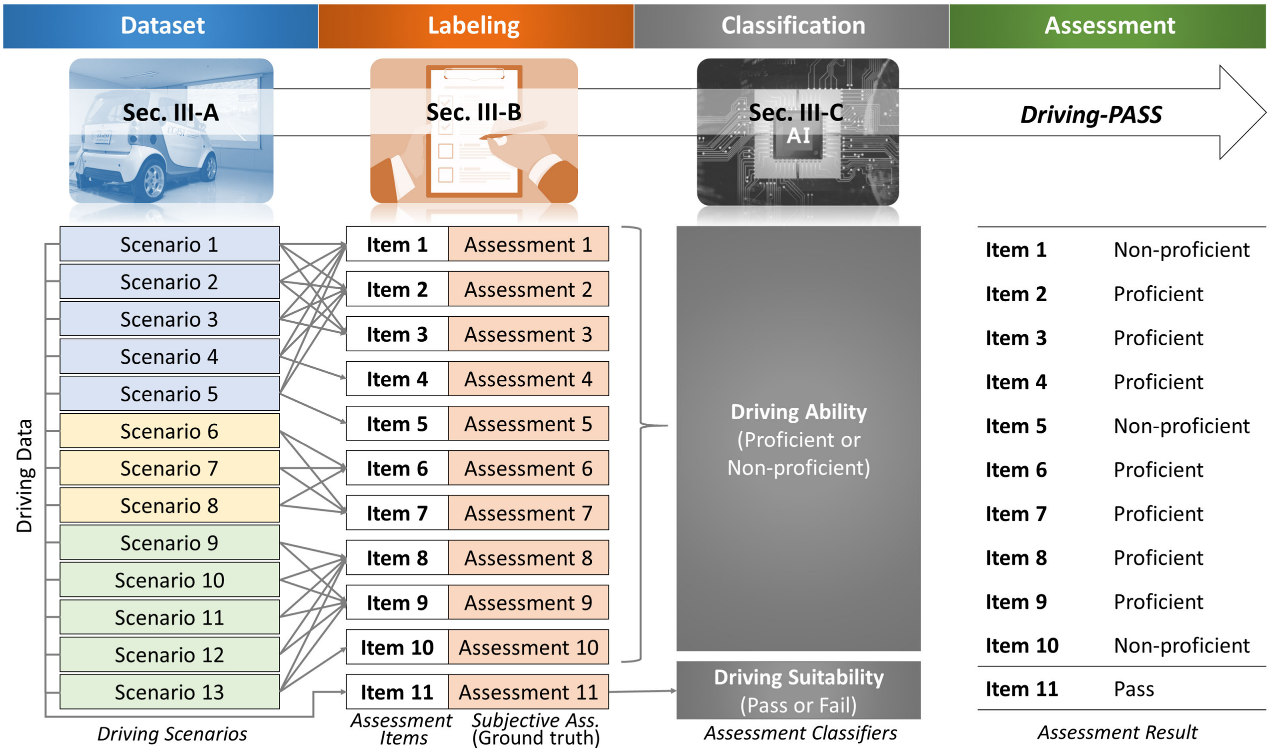

FIGURE 2. Overview of driving performance assessment system for stroke drivers.

abilities and a decision about driving suitability. For this goal, we propose assessment classifiers using driving profile data and subjective assessment results.

A. DATASET FOR DRIVING TEST

In this section, we construct a driving simulator environment and collect driving data in a simulator-based test.

1) EXPERIMENTAL SETUP

We use a STISIM DriveTM driving simulator for the driving test consisting of diverse driving scenarios. The driving simulator provides driving profiles reflecting on driver patterns and errors depending on pre-defined driving scenarios. A total of 29 time-series driving profiles are generated with a 30 Hz sampling rate as raw data.

For designing driving scenarios, we design a total of thirteen driving scenarios in three traffic environments (Urban, Highway, and Rural), as shown in Fig. 3. We take into account the appropriate driving test time (25 minutes on average) and properly configure the test's driving scenarios. The driving scenarios consist of two to three repetitions of basic driving skills related to speed control and steering control in the three different traffic environments. We also add driving events, considering cognitive & perceptual skills: three traffic light control events (green, green, and red) and three emergency control events. The rural scenarios are placed last because simulation sickness is the biggest in curves [61]. The other traffic environments are randomly arranged to form Path A and Path B. Participants randomly select Path A and Path B to perform the driving test. We construct a simulator environment by following the simulation settings of Oh *et al.* [62].

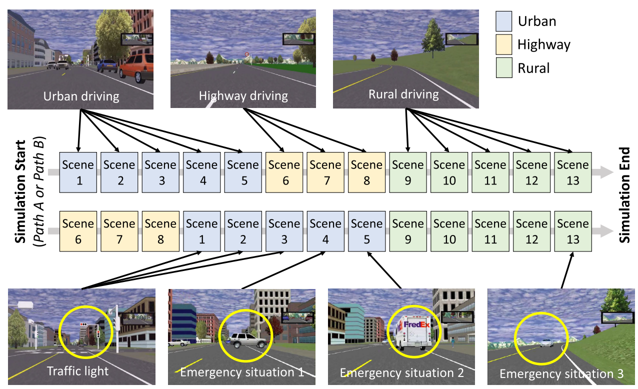

FIGURE 3. Driving scenario description in three traffic environments (Urban, Highway, Rural).

2) PARTICIPANTS

We recruit a total of twenty-seven participants consisting of eighteen stroke survivors and nine healthy people for this driving test. We note that Driving-PASS includes healthy people in the test to make a somewhat equal distribution between normal and abnormal driving when constructing general assessment items. The driving performance of stroke

TABLE 2. Driving scenario.

DS	Driving event	TE	Road T.
1	Traffic light (Green), Speed limit sign (70km/h)	Urban	1-S
2	Traffic light (Green), Speed limit sign (70km/h)	Urban	1-S
3	Traffic light (Red), Speed limit sign (70km/h)	Urban	1-S
4	A parked car suddenly enters and exits my lane.	Urban	1-S
5	A parked car comes into driver's lane, slowly goes, then leaves.	Urban	1-S
6	Speed limit sign (100km/h)	Highway	2-S
7	Speed limit sign (100km/h)	Highway	2-S
8	Speed limit sign (100km/h)	Highway	2-S
9	Left Curve sign, Speed limit sign (100km/h)	Rural	1-C
10	Right Curve sign, Speed limit sign (100km/h)	Rural	1-C
11	Left Curve sign, Speed limit sign (100km/h)	Rural	1-C
12	Right Curve sign, Speed limit sign (100km/h)	Rural	1-C
13	Oncoming car is heading into driver's lane.	Rural	1-C

DS: Driving Scenario, TE: Traffic Environment, 1-S: 1-way Straight road
2-S: 2-way Straight road, 1-C: 1-way Curvy road

patients tends to be biased toward an abnormal driving distribution. All of the stroke survivors satisfied with the minimum cognitive ability for driving, i.e., over 24 scores in a Korean version of Mini-Mental State Examination (K-MMSE) [63]. Healthy drivers have driving licenses with driving experience of over three years. Participants perform a simulator-based driving test consisting of thirteen driving scenarios.

3) DRIVING DATA

Driving scenarios are programmed to trigger an event when a driver goes to a specific location. We use driving data in a window (400 meters) that is the area of 200 meters before and after the specific location. In this way, driving data is segmented using a window s. The segmented driving data is used in subjective assessment and assessment classifiers. For subjective assessment, the segmented driving data is prepared as a video record by recording driving on the specific area using the playback function of the STISIM simulator. In the classification process in assessment classifiers, the segmented driving data (time-series data) is converted to a 3-dimensional matrix as an input image of the CNN. This approach is similar to stacking EEG signals (time-series data) and converting them into image data for analysis via CNN [64], [65].

B. LABELING

In this section, we design a driving performance evaluation method by human evaluators, which is used to set ground truth labels in Driving-PASS classifiers.

1) A DESIGN OF ASSESSMENT PROTOCOL

For designing a driving performance assessment for stroke drivers, we need to consider individual driving abilities in each driving situation and overall driving suitability. If a participant fails the driving test, we should be able to train the participant to pass the test after training the lack of specific driving abilities through the rehabilitation program.

In order to reflect the design goals, we propose a subjective driving evaluation method. Specifically, we design an assessment protocol with driving ability items in three different driving environments to evaluate basic maneuvering skills and cognitive & perception skills. The protocol also has a final decision item for determining driving suitability. Table 3 shows a subjective assessment sheet for the assessment protocol. Ten driving ability items consist of a five-score Likert-scale (0 to 4), and the final driving suitability item consists of binary decisions (Pass or Fail).

TABLE 3. Subjective assessment sheet.

Item	Description	TE	Skill T.	Score
Item 1	Speed Control	Urban	BD	0 1 2 3 4
Item 2	Steering Control	Urban	BD	0 1 2 3 4
Item 3	Traffic Light Control	Urban	CP	0 1 2 3 4
Item 4	Emergency Control 1	Urban	CP	0 1 2 3 4
Item 5	Emergency Control 2	Urban	CP	0 1 2 3 4
Item 6	Speed Control	Highway	BD	0 1 2 3 4
Item 7	Steering Control	Highway	BD	0 1 2 3 4
Item 8	Speed Control	Rural	BD	0 1 2 3 4
Item 9	Steering Control	Rural	BD	0 1 2 3 4
Item 10	Emergency Control 3	Rural	CP	0 1 2 3 4
Item 11	Driving Suitability	-	-	Pass or Fail

TE: Traffic Environment, T: Type, BD: Basic Driving skills
CP: Cognitive & Perceptual skills

We note that eleven assessment items are designed by considering thirteen driving scenarios. The relationship map between them is shown in Fig. 2. For example, speed control and steering control items (item 1, 2, 6, 7, 8, and 9) are linked to all driving scenarios in each traffic environment to evaluate overall basic driving abilities. Traffic control item (item 3) is linked to three driving scenarios since a driver passes three traffic lights (green, green, and red). Three emergency items (item 4, 5, and 10) are linked to one driving scenario to investigate whether a driver performs well in a specific hazardous situation. The final item (item 11) is linked to all driving scenarios, taking into account the driving performance for all driving scenarios to determine the final driving suitability.

2) SUBJECTIVE ASSESSMENT BY DRIVING EVALUATORS

To assess driving performance, we score the driving performance according to the opinion of driving evaluators.

We invite a total of ten driving evaluators (seven driving experts and three driving researchers). Driving experts are the experts with more than five years of experience in the field of driving performance assessment. Driving researchers consist of researchers who have less than five years of experience and conduct driving research, including human factors. We hide personal information, show the recorded video clips of twenty-seven drivers, and ask for the evaluation of the driving performance. The evaluators score each item according to their subjective opinions on the subjective assessment sheet.

To reliably assess each item's performance, we use the mean of multiple raters evaluating the same person. The method is used to increase reliability [66].

3) RELIABILITY ADJUSTMENT

In this section, we select the optimal raters in each item to improve reliability and use scores of selected raters for making ground truth labels in Driving-PASS.

Cronbach's alpha α is commonly used to assess the reliability or internal consistency. Cronbach's alpha α is interpreted according to the rule of thumb: $\alpha \geq 0.9$ is excellent, $0.9 > \alpha \geq 0.8$ is good, $0.8 > \alpha \geq 0.7$ is acceptable, $0.7 > \alpha \geq 0.6$ is questionable, $0.6 > \alpha \geq 0.5$ is poor, $0.5 > \alpha$ is unacceptable. In general, a score of more than 0.7 is usually acceptable. However, a higher alpha value of 0.90 has been recommended [67]. By using Cronbach's alpha α, it is possible to increase reliability by eliminating the poor performing raters [68].

In order to select the optimal raters, Driving-PASS has different policies for driving ability items and a driving suitability item. The driving ability items are designed to evaluate general driving abilities based on the general driver's safety knowledge. On the other hand, the driving suitability item is designed to determine the fitness to drive based on a qualified professional's experience and perspective due to safety issues on the actual road driving test.

For the driving ability items, the eliminating process is carried out until there is no further improvement in driving ability items' reliability. The items (item 1 to item 10) aim to maximize each item's reliability by selecting the optimal raters among all ten diving evaluators.

For the driving suitability item, we use the decision results only from seven driving experts. When determining whether an actual stroke patient is eligible for a driver's license, the evaluator puts slightly different weights on the driving performance evaluation items based on their experience and perspective. Therefore, we considered all experts' opinions to determine the *Pass* or *Fail* according to the majority vote.

Table 4 shows the reliability results after selecting the optimal raters in each item. After selecting the optimal raters, we use the mean of scores from selected raters as a performance score in the ability items. For the driving suitability item, we use the total number of *Pass* from seven driving experts.

TABLE 4. Reliability adjustment by selecting optimal raters.

Item	Original Cron.a	Filtered Cron.a	Selected Raters
Item 1	.892	.901	E1 E2 E3 E4 E5 E6 E7 R2 R3
Item 2	.931	.932	E1 E3 E4 E5 E6 E7 R1 R2 R3
Item 3	.966	.968	E1 E2 E3 E4 E5 R1 R2 R3
Item 4	.964	.974	E1 E2 E3 E4 R1 R2 R3
Item 5	.960	.961	E1 E2 E3 E4 E5 E6 R1 R2 R3
Item 6	.890	.890	E1 E2 E3 E4 E5 E6 E7 R1 R2 R3
Item 7	.965	.965	E1 E2 E3 E4 E5 E6 E7 R1 R2 R3
Item 8	.948	.951	E1 E2 E4 E5 E6 E7 R1 R2 R3
Item 9	.955	.955	E1 E2 E3 E4 E5 E6 E7 R1 R2 R3
Item 10	.917	.925	E1 E2 E5 E6 E7 R1 R2 R3
Item 11	-	.932	E1 E2 E3 E4 E5 E6 E7

E: Expert, R: Researcher, Cron.a: Cronbach's alpha

C. ASSESSMENT CLASSIFIERS

In this section, we introduce how to design assessment classifiers by using the segmented driving data in Sec. III-A3 and the subjective assessment results in Sec. III-B. The detailed process of data processing is shown in Fig. 4.

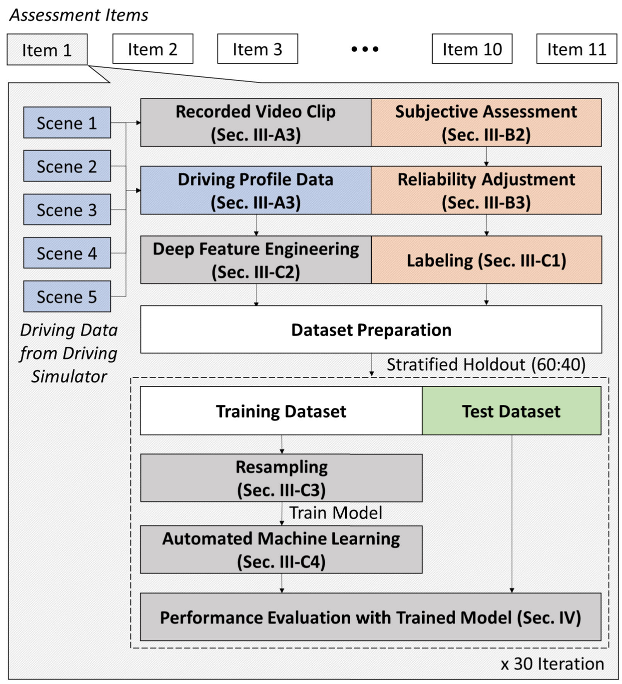

FIGURE 4. The detailed process of data processing in Driving-PASS.

In more detail, deep feature engineering (Sec. III-C1) and labeling (Sec. III-C2) processes are performed to construct the dataset. After that, we evaluate the classification performance of eleven assessment classifiers in Driving-PASS by thirty times repeated *Stratified Holdout*. *Holdout* technique randomly splits the dataset into a training dataset and a test dataset with a ratio of 60:40. *Stratified* sampling preserves the percentage of samples for each class in the original dataset.

Eleven assessment classifier models are trained using a training dataset. We add a resampling method (Sec. III-C3) to increase the classification performance and construct the classifiers using Automated Machine Learning (AutoML) tool in Matlab (Sec. III-C4). The test dataset is applied to the trained model to verify the final classification performance. The evaluation results are discussed in Sec. IV.

1) LABELING

In the previous process, we select the best evaluators for each item and estimate the performance results (the mean of scores m and the total number of Pass t) from those evaluators.

Driving-PASS aims to classify not only insufficient driving abilities but also driving suitability. Therefore, we define two binary classes in driving ability items and a driving suitability item to achieve these purposes.

In driving ability items, we define two binary classes, i.e., Proficient and Non-proficient. Based on the mean of scores m for 27 participants in driving ability items (item1 to item10), we can categorize them into two classes using a fixed score. For setting the fixed score, we use a fixed score of 2.8. When converting the 5-score Likert-scale (0 to 4) to 100 points, the proficiency is defined as 70 points or more (origin Likert-scale score is 2.8). The on-road driving exam uses a fixed threshold of 70 points for passing criterion [69]. We use the criterion for classifying insufficient driving abilities in our system. The class for driving ability items $Class_A(m)$ is labeled according to the mean of scores m, as shown in Eq. 1. Labeled classes are used as ground-truth labels in Driving-PASS.

$$Class_A(m) = \begin{cases} \text{Proficient}, & \text{if } m \geq 2.8 \\ \text{Non-proficient}, & \text{otherwise} \end{cases} \tag{1}$$

Driving suitability item is evaluated according to the majority rule. If more than four evaluators determine a person as pass, the person passes. Otherwise, the person is evaluated as a failure. Eq. 2 shows that the class for driving suitability item $Class_S(t)$ is labeled according to the total number of Pass t. Additionally, we include driving data from healthy people in our datasets. When all healthy people's information is hidden, all healthy drivers are considered to pass according to the criterion's driving suitability. We confirm that there is no false decision on the criterion in healthy people.

$$Class_S(t) = \begin{cases} \text{Pass}, & \text{if } t \geq 4 \\ \text{Fail}, & \text{otherwise} \end{cases} \tag{2}$$

2) FEATURE ENGINEERING

STISIM driving simulator provides driving profile data consisting of 29 time-series data as raw data. Using the data, we can extract the driving patterns for predefined scenarios. The driving patterns appear in the form of driving performance metrics, a.k.a. features. Depending on metric types, we can generate many driving performance metrics, e.g., mean speed, a standard deviation of speed, and maximum speed in speed metrics [70]. The technical problem is that designing driving performance metrics for specific research purposes is somewhat subjective and has limitations due to the design of handcrafted features. For example, optimal driving performance metrics are different for each driving scenario and also depend on scenario size, such as whether to view the scenarios individually, regionally, or globally.

CNN has been shown to excel in a wide range of computer vision tasks, and approaches to leverage proven CNN models for new applications have been developed as one of the key CNN-based researches. "Deep features" extracted from pre-trained CNN models are applied to machine learning classifiers (e.g., ensemble, support vector machine, and decision tree classifier) as the input data for medical applications, such as tuberculosis [71], malaria parasite [72], lung cancer survivor [73], and cataract detection [74]. Although pre-trained CNN models have been designed and trained for image classification using millions of ImageNet examples, this approach contributes to performance improvements in different domains for specific medical applications.

In this work, we use pre-trained CNN models as a tool for feature extraction to address the limitations of handcrafted features. We select five pre-trained CNN models in this work: Resnet18, Inceptionv3, Resnet50, Resnet101, and Inception-ResNet-v2 (IncResV2). Resnet18 [75] and Inceptionv3 [76] are a well-known CNN model architectures demonstrated in ILSVRC (ImageNet Large Scale Visual Recognition Challenge). The remaining models are those with improved performance by changing the size and structure of the Resnet model and Inception model [77], [78]. Table 6 details the depth, parameter size, and input size of these CNN models. We investigate how the performance changes as the structure of the CNN model increases.

Feature extraction: deep features are extracted from the activation layer of a pre-trained CNN model. How to construct input data from a driving simulator and generate deep features are described in detail below.

Step 1: *Construct input data*: Input data for these CNN models is a 3-dimensional (3D) image data. We only use raw driving profiles that represent driving patterns in specific driving scenarios. Therefore, we select 21 raw data from 29 raw driving profile data, as shown in Table 5. After that, we generate deep features in each driving scenario from four pre-trained CNN models by using the raw data. Pre-processing for deep features works as follows: we align 21 normalized raw driving profile data into a 3D matrix $[s \times f \times 3]$, where simulation sample s and features f are determined in Sec. III-A3 and Sec. III-C2, respectively.

Step 2: *Resize the input data*: In order to use a pre-trained CNN model, the size of input data must be the same as that of the input data of the CNN model. Therefore, we resize the 3D matrix tailored to the input size of the individual CNN model before feature extraction. The individual input size of CNN models is described in Table 6. For resizing the input data, we use a function *imresize* provided in Matlab.

Step 3: *Generate deep features*: Deep features are generated from the activation layer of pre-trained CNN models using a function *Activations* in the Deep learning toolbox of Matlab. For example, the deep features of Resnet18 are extracted from the *pool5* layer and consist of 512 features for scenario 1, as shown in Fig. 5. The name of the activation layer and the number of deep features in four pre-trained CNN models are described in Table 6.

Step 4: *Concatenate deep features*: Some items among driving ability items, such as speed control, are related to several driving scenarios (scenarios 1 to 5). To consider this relationship, we generate input data by concatenating deep features in the related scenarios.

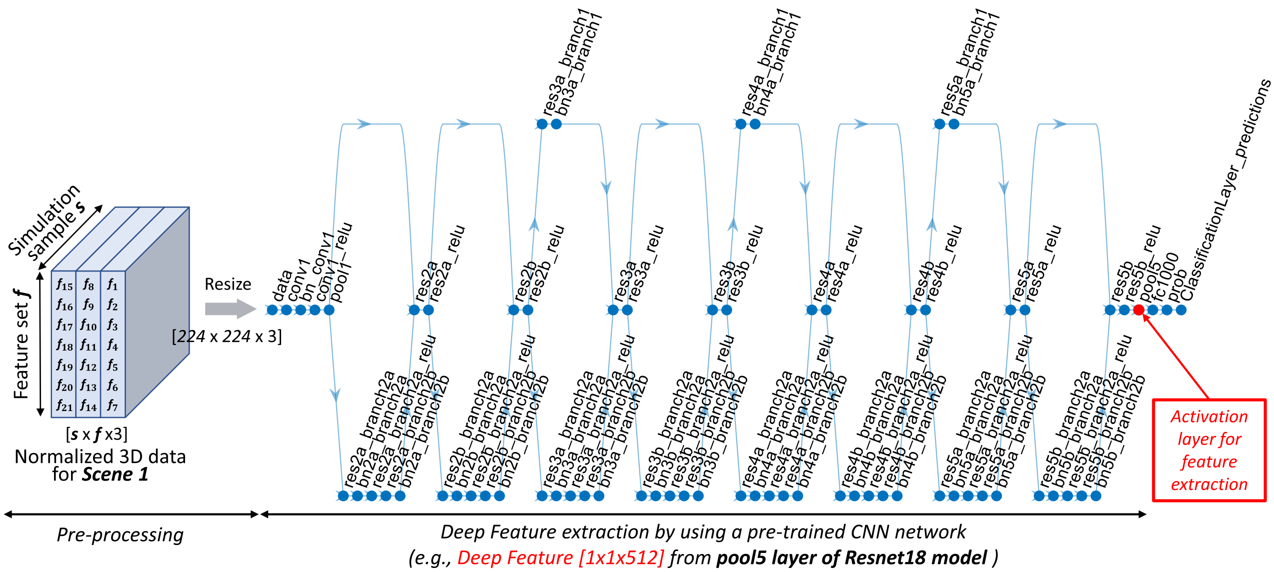

FIGURE 5. Feature extraction by using a pre-trained CNN model.

TABLE 5. Description for Selected Raw Driving Profile Data in STISIM driving simulator.

Num.	Driving Profile	Measurement Unit
1.	Driver's longitudinal acceleration	$feet/second^2$
2.	Driver's lateral acceleration	$feet/second^2$
3.	Driver's longitudinal velocity	$feet/second$
4.	Driver's lateral velocity	$feet$
5.	Driver's lateral lane position with respect to the roadway dividing line	$feet$
6.	Vehicle curvature	$1/foot$
7.	Current roadway curvature	$1/foot$
8.	Vehicle heading angle	$degrees$
9.	Steering wheel angle input	$degrees$
10.	Longitudinal acceleration due to the throttle	$feet/second^2$
11.	Longitudinal acceleration due to the brakes	$feet/second^2$
12.	Running compilation of the crashes that the driver has been involved in	$counts$
13.	Driver's longitudinal velocity	$miles/hour$
14.	Steering input counts (Actual raw input)	$counts$
15.	Throttle input counts (Actual raw input)	$counts$
16.	Braking input counts (Actual raw input)	$counts$
17.	Steering wheel rate	$radians/second$
18.	Minimum time to collision between the driver and all vehicles in the driver's direction	$seconds$
19.	Minimum range between the driver and all vehicles in the driver's direction	$feet$
20.	Minimum time to collision between the driver and all vehicles opposing the driver's direction	$seconds$
21.	Minimum range between the driver and all vehicles opposing the driver's direction.	$feet$

For example, in the case of Resnet18, input data for an assessment item 1 consists of five concatenated deep features df with the size of [1 × 2560] that are extracted from five driving scenarios, i.e., $[df_1, df_2, df_3, df_4, df_5]$. The input data for a driving suitability item consists of thirteen concatenated deep features with the size of [1 × 6144] that are extracted from all thirteen driving scenarios, i.e., $[df_1, df_2, \ldots, df_{12}, df_{13}]$.

TABLE 6. Description of Pre-trained CNN Models and Feature Information for Feature Extraction.

CNN model	Depth	Parameter size[million]	Input size	Feature extraction	
				Act. layer	Feat. num
Resnet18	18	11.7	224x224x3	'pool5'	512
Inceptionv3	48	23.9	299x299x3	'avg_pool'	2048
Resnet50	50	25.6	224x224x3	'avg_pool'	2048
Resnet101	101	44.6	224x224x3	'pool5'	2048
IncResV2	164	55.9	299x299x3	'avg_pool'	1536

Act. layer: Activation layer, and Feat. num: Feature number

Feature selection: Pre-trained CNN models are used to extract deep features, but too many features increase the computational burden on the machine learning classifier, resulting in deterioration of classification performance. To overcome this problem, we add feature selection method in our system. The feature selection identifies relevant features that are useful for determining the final class, and discards features that are irrelevant and merely occupying the entire dimension of the problem space. In this work, we perform a chi-square test on the input data set to select the important features. Matlab 2020a provides a function *fscchi2* for feature selection. We use only deep features with a score higher than 0 calculated by this function.

3) RESAMPLING

In addition to feature engineering, it is required to balance training dataset for the performance of the machine learning algorithms [79]. We configure the dataset to perform binary classification on eleven assessment items, but some items do not have the same number of the dataset in each class, resulting in an imbalanced dataset. In general, imbalanced datasets are easily found in medical applications due to the lack of rare disease datasets [80]. For dealing with the imbalanced dataset problems, resampling strategies such as under-sampling and over-sampling are widely used. Since we do not have many datasets in this work, we focus on the oversampling techniques and use one resampling algorithm in our work, i.e., Synthetic Minority Over-sampling Technique (SMOTE).

SMOTE first randomly selects a minority class instance a and finds its k-nearest neighbors. Then, a synthetic point is created anywhere on the line between a and randomly selected one of the neighbors b in the feature spaces [81]. To implement SMOTE, we use "Data Mining with R" (DMwR) package in R programming [82]. In the DMwR package, it supports SMOTE for classification and regression. We create a file containing a training dataset in Matlab, load it to perform SMOTE for classification in R programming, and then import the file generated from R programming back into Matlab to perform the next procedure. For parameter settings of SMOTE, we set "perc.over = 100". It means over-sampling the minority class to the number of the majority class. We also select the optimal number of k achieving the best classification performance by investigating k from 1 to 10.

4) AUTOMATED MACHINE LEARNING

For the eleven assessment classifiers in Driving-PASS, we use Machine Learning (ML) classifiers. Building a good ML model requires a lot of manual trial and error in model selection and hyper-parameters tuning. With advances in ML techniques, these manual tasks are automated, which is called AutoML. AutoML eliminates the manual steps and builds an accurate model automatically in a single step. That is, AutoML identifies the best model among many available models (e.g., discriminant analysis, k-nearest neighbor, linear, and SVM) and then tunes its hyper-parameters to optimize performance by applying Bayesian optimization. To implement AutoML in Driving-PASS, we use a function *fitcauto* to select a classification model with optimized hyper-parameters automatically. Note that we focus on a feature extraction method using pre-trained CNN models and a resampling method. In this work. Developing a new ML classifier and comparing it with other ML classifiers are beyond the scope of this paper.

IV. EVALUATION

In this section, we evaluate the classification performance in a total of eleven assessment items consisting of ten driving performance classifiers and one decision classifier. For the performance evaluation, we perform thirty times repeated Stratified Holdout. We compare the performance of deep features from five pre-trained CNN models and select deep features that meet the best performance in each assessment item.

A. EVALUATION METRICS

To evaluate the classification performance, we introduce evaluation metrics in this section. Driving-PASS consists of eleven items: ten decision items (Proficient or Non-proficient) and one decision item (Pass or Fail). In the following, we describe the evaluation metrics used in our system.

Precision (*Pre*) is defined as the number of true positives (T_P) over the number of true positives (T_P) plus the number of false positives (F_P), as shown in Eq. 3. *Pre* is the proportion of positive cases that are correctly identified.

$$Pre = \frac{T_P}{T_P + F_P} \tag{3}$$

Recall (*Rec*) is defined as T_P over T_P plus the number of false negatives (F_N), as shown in Eq. 4. *Rec* is the proportion of actual positive cases that are correctly identified.

$$Rec = \frac{T_P}{T_P + F_N} \tag{4}$$

Accuracy (*Acc*) is defined as T_P plus T_N over the sum of all binary performance metrics, i.e, T_P, T_N, F_P, and F_N, as shown in Eq. 5. *Acc* is the proportion of the total number of predictions are correct.

$$Acc = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \tag{5}$$

F1-score ($F1$) is the harmonic mean of precision (*Pre*) and recall (*Rec*), combining two performance metrics into one metric, as shown in Eq. 6. This metric is one of the most used metrics for handling imbalanced datasets.

$$F1 = 2\frac{Pre \cdot Rec}{Pre + Rec} \tag{6}$$

Eleven assessment items in Driving-PASS consists of binary items, i.e., two classes. To evaluate Driving-PASS's overall performance, we use a simple arithmetic mean of four metrics of the two classes in each item. The average performance metrics are formed by averaging the five performance metrics in the two classes ($N = 2$), a.k.a., Macro-average. The micro average indicates that each class is of equal importance. We use five metrics as performance metrics by micro-averaging, as follows:

$$mPre = \frac{1}{N}\sum_{k=1}^{N} Pre(k) \tag{7}$$

$$mRec = \frac{1}{N}\sum_{k=1}^{N} Rec(k) \tag{8}$$

$$mAcc = \frac{1}{N}\sum_{k=1}^{N} Acc(k) \tag{9}$$

$$mF1 = \frac{1}{N}\sum_{k=1}^{N} F1(k) \tag{10}$$

In our dataset, some items consist of imbalanced datasets, where classes are not evenly distributed. In order to address

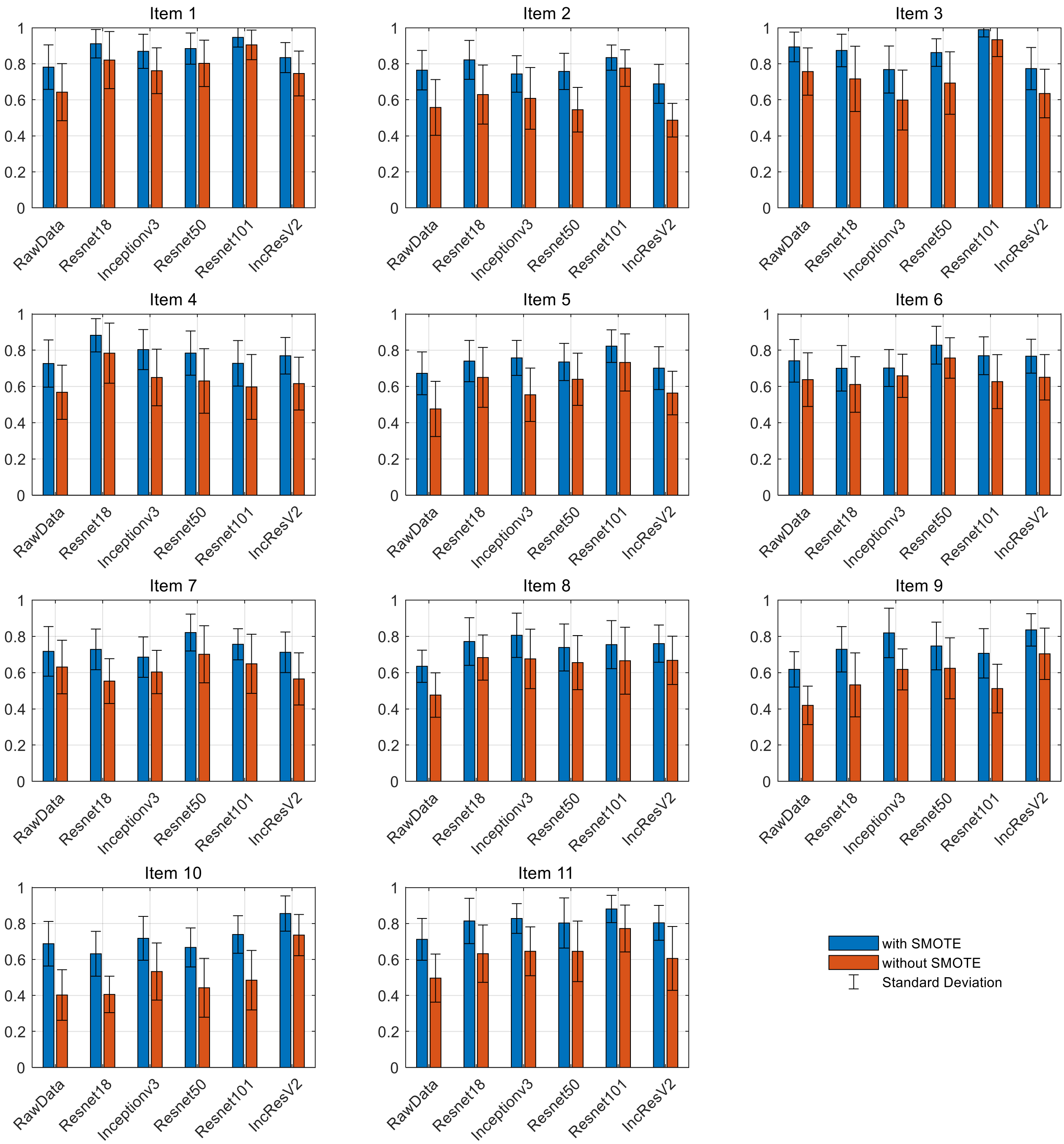

FIGURE 6. Performance evaluation ($mF1$) considering five deep features of Pre-trained CNN models and a resampling method (SMOTE).

this imbalanced dataset problem, we evaluate classification performance by using $mF1$ to select the best classification method in each item. After that, we also evaluate the classification performance with other performance metrics.

B. CLASSIFICATION PERFORMANCE EVALUATION

This section evaluates the classification performance with thirty times repeated Stratified Holdout, taking into account deep features of five pre-trained CNN models (Resnet18, Inceptionv3, Resnet50, Resnet101, and IncResV2) and a resampling algorithm (SMOTE).

Fig. 6 shows the classification performance evaluation ($mF1$) considering five deep features and SMOTE. Classification performance is significantly affected by which features are used. The performance is somewhat satisfactory when using the raw data without a feature extraction method using pre-trained CNN models, but it does not show the best

TABLE 7. Summary of performance evaluation in Driving-PASS.

Item	Description	Traffic Environment	Road Type	Skill Type	Selected DS	Performance Metrics $mF1$	$mAcc$	$mRec$	$mPre$	Selected DF
Item 1	Speed Control	Urban	1-S	BD	1,2,3,4,5	0.95±0.05	0.95±0.05	0.95±0.06	0.96±0.04	Resnet101
Item 2	Steering Control	Urban	1-S	BD	1,2,3,4,5	0.83±0.07	0.84±0.07	0.84±0.07	0.86±0.07	Resnet101
Item 3	Traffic Light Control	Urban	1-S	CP	1,2,3	0.99±0.04	0.99±0.04	0.99±0.03	0.99±0.03	Resnet101
Item 4	Emergency Control 1	Urban	1-S	CP	4	0.88±0.09	0.90±0.08	0.89±0.09	0.90±0.09	Resnet18
Item 5	Emergency Control 2	Urban	1-S	CP	5	0.82±0.09	0.83±0.09	0.83±0.09	0.84±0.09	Resnet101
Item 6	Speed Control	Highway	2-S	BD	6,7,8	0.83±0.10	0.83±0.10	0.83±0.10	0.84±0.10	Resnet50
Item 7	Steering Control	Highway	2-S	BD	6,7,8	0.82±0.10	0.82±0.10	0.82±0.10	0.84±0.10	Resnet50
Item 8	Speed Control	Rural	1-C	BD	9,10,11,12,13	0.81±0.12	0.81±0.12	0.83±0.11	0.83±0.11	Inceptionv3
Item 9	Steering Control	Rural	1-C	BD	9,10,11,12,13	0.84±0.09	0.85±0.09	0.88±0.07	0.85±0.08	IncResV2
Item 10	Emergency Control 3	Rural	1-C	CP	13	0.86±0.10	0.86±0.10	0.87±0.09	0.88±0.09	IncResV2
Item 11	Driving Suitability	-	-	-	All DS	0.88±0.08	0.89±0.07	0.88±0.08	0.90±0.07	Resnet101

DS: Driving Scenario, DF: Deep Features, BD: Basic Driving skills, CP: Cognitive & Perceptual driving skills
1-S: 1-way Straight road, 2-S: 2-way Straight road, 1-C: 1-way Curvy road

performance. Evaluation results demonstrate that the feature extraction method with pre-trained CNN models effectively classifies two binary classes in each item. In most cases, using a pre-trained CNN model for feature extraction improves the classification performance.

The best classification performance is seen on deep features, and the best CNN models for the deep feature extraction depends on the assessment items. For driving ability items, the best deep features are different depending on the traffic environments. For example, deep feature (DF) using Resnet 101 is the most performance in Urban, DF using Resnet 50 in Highway, and DF using IncResV2 in Rural, respectively. As an exception, DF using resnet18 and DF using Inceptionv3 perform best in items 4 and 8, respectively. For a driving suitability item, DF using Resnet101 shows the best classification performance.

Besides, applying the resampling algorithm (SMOTE) improves classification performance ($mF1$) by 5∼71% in all eleven assessment items. The results indicate that evenly distributing each class in the training dataset significantly impacts classification performance.

Table 7 shows a summary of the performance evaluation that considers all performance metrics ($mF1$, *mAcc*, *mRec*, and *mPre*) in eleven assessment items after finally selecting the best deep feature with SMOTE in each item. The performance metrics for *mAcc*, *mRec*, and *mPre* also show similar performance patterns to $mF1$. Besides, the selected deep features are relevant to driving simulation environments, such as traffic environments and road types, not driving skill types.

In summary, we compensate for the limitations of handcrafted features and imbalanced dataset problems by carefully selecting deep features in each item and using a resampling algorithm. Evaluation results show that Driving-PASS shows high classification performance over $mF1$ of 0.81 in all assessment items.

V. DISCUSSION

The demand for accurate and reliable evaluation of stroke drivers is increasing due to accidents caused by them. Nevertheless, the lack of institutional control for stroke drivers in the motor vehicle licensing authority increases the risk of driving accidents. Our system offers an alternative to stroke driver evaluation since the driving simulator test has key advantages in identifying risks to driving safety compared to other driving evaluation methods [83].

Driving-PASS is designed to address the safety concerns of stroke drivers returning to driving by automatically evaluating driving abilities and driving suitability. Assessment results of Driving-PASS provide not only information about insufficient driving abilities for driving rehabilitation but also a pre-screening judgment of whether a stroke survivor can perform the on-road test. Our system serves as a pre-screening tool and ultimately improves stroke drivers' safety and other road drivers.

There are some limitations in this work. First, we use a machine learning approach rather than using state-of-the-art deep learning technologies. Deep learning technologies are based on a data-driven approach that requires many datasets to train deep learning models. Because of the small number of driving datasets, we select one of the deep learning techniques in our work that uses relatively small datasets but shows good performance. We will extend our work to develop more sophisticated classifiers using deep learning techniques by collecting large driving datasets in future work.

Second, for driving ability items, our system's evaluation results do not reveal the cause of the driving error. They only provide information about problematic items. Since Driving-PASS is trained to classify binary decisions, such as Proficient vs. Non-proficient, there are limitations to interpret the detailed analysis of the problematic items. One solution is to divide more subitems in each ability item and analyze the subitems based on large driving data sets in terms of factor analysis. However, such simulator analysis has limitations since only the neuropsychometric test clearly reveals the reasons for driving errors [84]. Despite the limitations, a driving rehabilitation program improves driving performance skills such as crashes and speed [85]. Repeated driving training also demonstrates to help driving skills [86]. Considering the problematic items, we will develop an effective driving rehabilitation program tailored to individual patients in the future.

Lastly, there are twenty-seven driving data for the driving simulator test and no on-road test results in our dataset. Therefore, driving suitability is limited to the simulation test. In our work, driving suitability means a preliminary examination to determine whether an on-road test is suitable. Ultimately, the on-road test determines the fitness-to-drive on the road. We plan to extend our work to judge actual driving suitability using only the simulator test results by collecting the results of the on-road test.

VI. CONCLUSION

After a stroke, an accurate assessment of driving is essential for driving safety. A driving simulator-based assessment is a promising tool because of the benefits of effectively and safely identifying risks to driving safety. As an effort to provide such a system, we propose Driving-PASS based on a driving simulator assessment.

We construct a simulator driving test consisting of thirteen driving scenarios design a subjective assessment consisting of ten driving ability items and one decision item. Using the driving data from the driving simulator and evaluation results from ten driving evaluators, we build eleven assessment classifiers, the core engine of Driving-PASS. Technically, we compensate limitations of handcrafted feature design and imbalanced dataset problems by using a feature extraction method using pre-trained CNN models and a resampling method.

Evaluation results demonstrate that Driving-PASS classifies problematic driving ability items (item 1∼10) and determines driving suitability item (item 11) with high classification performance. We envision that Driving-PASS will be a pre-screening tool for assessing driving performance, ultimately improving road safety.

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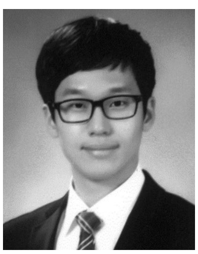

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