# Literature Survey

## Topic:

**Intelligent Vehicle Damage Assessment and Cost Estimator for Insurance Companies**

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## Title 1: Car Damage Assessment for Insurance Companies

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### Abstract:

*I*n the proposed solution. In Advanced solution helps to speed up the claiming process sufficiently. Analysis of the damaged vehicle that can be automatically claiming insurance that takes human resource, time and effort. Image processing and machine learning techniques are analysing the vehicle damage Consider a situation, if a person is driving a car they met an accident the vehicle owner can taken a few photos of the damaged car from a mobile phone that can be send to the insurance company and can just upload the photos to the system. The system can analyse the damage, severity of the damage as well as location of the damage. In this proposed project the insurance company can machine-driven the car damage analysis process without the need for humans to analyse the damage done to the car. Therefore, it is a very challenging task for quality of computer vision techniques and also Machine learning technologies


### Introduction:

In today's world, Vehicles are increasing heavily. Because of increasing the vehicles, accidents are very common because the peoples are driving a car very fastly on the road. The people claim the money for repair the car through vehicle insurance when the accident happens. Because of incorrect claims, the company behaves badly and doesn't make payments currently. This happens due to claims leakage, the claims leakage refers to the difference between the amounts secured by the company to the amount that company should have secured based on the claims. Still the damage to the car is examined clearly and it will take more time to claim the process according to the company policy. Although the company does one's best to speed up the claiming process delay. Differentiate the proposed system that is maybe speed up the car damage that can be check in process. Just by sending the image containing a damaged car and can system performs car damage detection in a minute rather than hours if it is inspected visually. The system can utilizes machine learning approach as well as computer vision to decide the damage analysis, location of the damage as well as severity of the damage

## PROPOSED METHODOLOGY:

Detect the car damage using photo taken at the accident scene is very useful to reduce the cost of processing insurance claims, as well as provide greater convenience for vehicle users. The following methods are used in the proposed system.

1. Dataset Explanation.
2. Describing the level of damage.
3. CNN Model.
4. VGG16 Algorithm.

## Dataset Explanation

Data preparation is very costly depending on the demand of marking the data.VGG16 can be used to need as a true image in an input. Cross-validation is an approximate for our models to takes a more time since, it is very costly to train the VGG16 for many years. Consequently split the dataset arbitrarily into distinct set for training and validation. Car is to train for multiple times. At the end train and test can be split for similar images. In this dataset we use more different types of car images. Report our three collected datasets are following.

- Image Net dataset - Vehicle
- Dataset - All the three dataset are contained train and validation of damaged and undamaged cars.

## Describing the Level of Damage

Damaged car can be defined by their incidence. We think about each damaged part into small, average, severe. The categorization of the damaged car levels as follows.

- Small Damage - creaks in headlight
- Average Damage - Damage in car doors.
- Severe Damage - damage of air bags.

## CNN Model

CNN is one of the neural network it is used for processing the image and segmentation of the image. In this project we use a convolution neural network model for detect the image contains a car. CNN is also used to analyses the damage of the car.

## VGG16 Algorithm

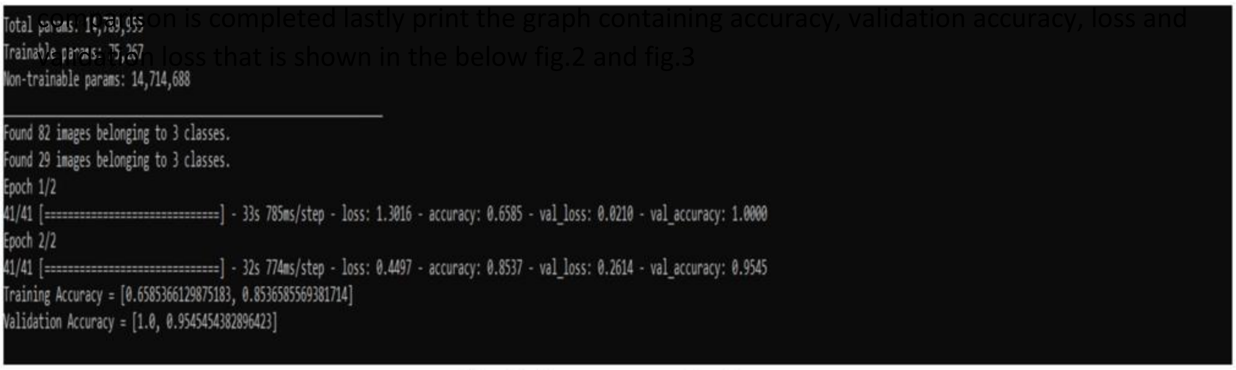
The Image Net Large Scale Visual Recognition Challenge is one of the visions of computer. They contain two jobs. Initial is to detect things within an image called object localization. Next is to classifying the images called image classification.

CNN is the one of the best vision model planning. In VGG16 contains four layers they are convolution, max pooling, and fully connected softmax. In this algorithm 16 refers to contain 16 layer

In this diagram they tell about the working of the project. In the first block they took a damaged car as an input. Once this image is given as an input after that they apply neural network is to be interesting for detecting the image hold the car. Car detection is done perfectly, then goes to the next step or else does not go to the next step. Detection of the car is done perfectly then analyse the damage of the car by applying the neural network. Check for car it may contains any damage then go to next step or does not proceed to the next step. If the damage is detect in the system estimate the location in the damaged car like front, back, and side of the car. They give the accurate result for the location of damaged car, and also give severity like minor, moderate, and severe. In this system they carry out some functions including car detection, car damage analysis, predict the location of the damaged car and also car damaged severity.

## EXPERIMENTAL RESULTS

First we have to train the image contains a car. The data contains three classes namely train, test and validation. Trained image is compare with the test image. Car as to be trained for many times by using epochs which means how many times the algorithm can work between the whole training dataset. In this graph they can taken only two times of running the algorithm. Finally the comparison is completed lastly print the graph containing accuracy, validation accuracy, loss and validation loss that is shown in the below fig.2 and fig.3



```
Total params: 14,789,955
Trainable params: 75,267
Non-trainable params: 14,714,688

Found 82 images belonging to 3 classes.
Found 29 images belonging to 3 classes.
Epoch 1/2
41/41 [==============================] - 33s 785ms/step - loss: 1.3016 - accuracy: 0.6585 - val_loss: 0.0210 - val_accuracy: 1.0000
Epoch 2/2
41/41 [==============================] - 32s 774ms/step - loss: 0.4497 - accuracy: 0.8537 - val_loss: 0.2614 - val_accuracy: 0.9545
Training Accuracy = [0.6585366129875183, 0.8536585569381714]
Validation Accuracy = [1.0, 0.9545454382896423]
```

Fig. 2: Accuracy result of car

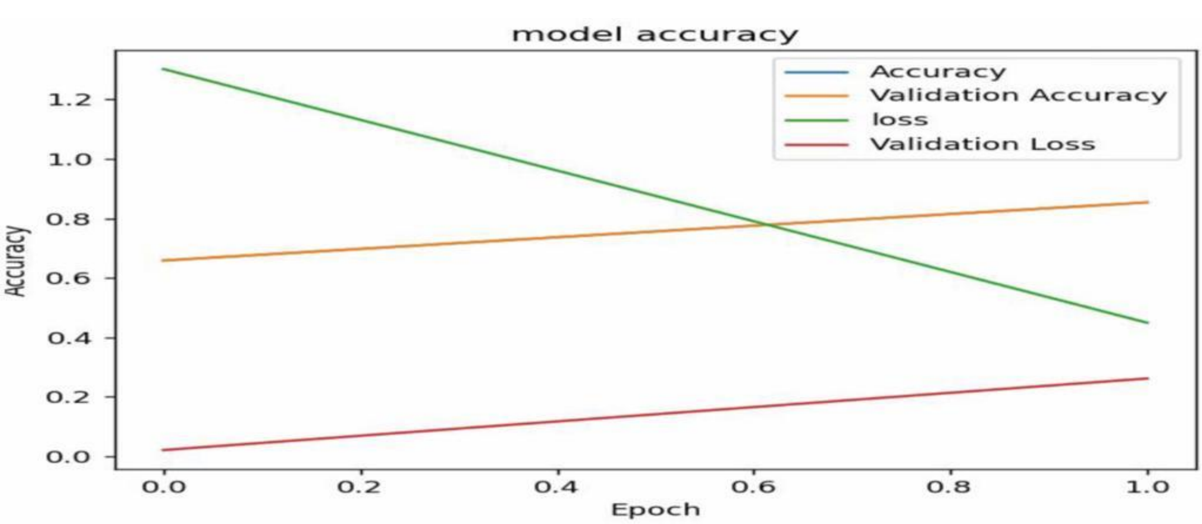



Fig. 3: Line graph of model accuracy

# Title 2: Car Damage Assessment for Insurance Companies

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## Abstract

Over the last few years, for the auto insurance claims process, improvements in the First Notice of Loss and rapidity in the investigation and evaluation of claims could drive significant values by reducing loss adjustment expense. Image based vehicle insurance processing is an important area with large scope for automation. In this report we are going to consider the problemof car damage classification, where some of the categories can be fine-granular. We explore deep learning-based techniques for this purpose. Success in this will allow some cases to proceed without human surveyor, while others to proceed more efficiently, thus ultimately shortening the time between the first Notice of Loss and the final payout. In the proposed car damage classification model initially, we try directly training a CNN. However, due to small set of labeled data, it does not work well. Then, we explore the effect of domain specific pre-training followed by fine-tuning. Finally, we experiment with transfer learning and ensemble learning. Experimental results show that transfer learning works better than domain specific fine-tuning. We achieve accuracy of 89.5% with combination of transfer and ensemble learning. Followed by the estimate damage cost calculation according the prediction of damaged car parts Key Words: Car damage classification, CNN, transfer learning, convolutional auto-encoders

## INTRODUCTION

Currently, AI is advancing at a great pace and deep learning is one of the contributors to that. It is good to understand the basics of deep learning as they are changing the world we live. Deep learning is a sub-field of machine learning dealing with algorithms inspired by the structure and function of the brain called artificial neural networks. In other words, It mirrors the functioning of our brains Deep learning algorithms are similar to how nervous system structured where each neuron connected each other and passing information. One of the differences between machine learning and deep learning model is on the feature extraction area. Feature extraction is done by human in machine learning whereas deep learning model figures out by itself Today, in the car insurance industry, a lot of money is wasted due to claims leakage. Money lost through claims management inefficiencies that ultimately result from failures in existing processes (manual and automated). In other words, it's the difference between what you did spend and what you should have spent on a claim. The cause can be procedural, such as from inefficient claim processing or improper/errant payments, or from human error, such as poor decision-making, customer service, or even fraud. Claim Leakage is often discovered through an audit of closed claim files. CNN is used as the default model for anything to deal with images. Hence in this project, we employ Convolutional Neural Network (CNN) based methods for classification of car damage types. Specifically, we consider common damage types such as bumper dent, door dent, glass shatter, headlamp broken, tail lamp broken, scratch and smash. Nowadays there are papers that have mentioned the use of Recurrent Neural Network (RNN) for the image recognition. Traditionally RNNs are being used for text and speech recognition. According to study after experimenting with many techniques such as directly training a CNN, pre-training a CNN using auto encoder followed by fine-tuning, using transfer learning from large CNN's trained on Image Net and building an ensemble classifier on top of the set of pre-trained classifiers. We observe that transfer learning combined with ensemble learning works the best.

# Proposed Work

The overall Damage Assessment for Car Insurance (DACI) can be divided in four parts:

¬ Collecting Datasets

¬ Training and Testing Of Datasets

¬ Backend

● Collecting Datasets

We have collected ten commonly observed types of damages such as Bumper, door, door glass, grille, headlamp, hood, mirror, roof, taillamp, and windshield in addition we also collected some images which does not belong to damage class, some images were collected from web and somewhere manually annotated.

● Training and Testing of Datasets

3000 plus images were taken for training and 200-300 for testing. we synthetically enlarged the dataset approx. five times by appending it with random rotations (between -20 to 20 degrees) and horizontal flip transformations. For the classification experiments, the dataset was randomly split into 80%-20% where 80% was used for training and 20% was used for testing.

● Backend

We created separate python programs for each of those commonly observed car parts for recognizing in image whether that car part is damaged or not, and will tell if it is not present in image.

ϖ Generating a CNN model

The created python programs for each of car parts were used to train the CNN model for recognizing in image whether that car partis damaged or not, and will tell if it is not present in image. The model consist of ten layers Conv1-Pool1-Conv2-Pool2-Conv3-Pool3- Conv4Pool4-FC-Softmax where Conv, Pool, FC and SoftMax denotes convolution layer, pooling layer, fully connected layer and a SoftMax layer respectively. Each convolutional layer has 16 filters of size 5 × 5. A RELU non-linearity is used for every convolutional layer. The total number of weights in the network are approx. 423K Car image will be passed through all these 10 models one by one, and each model will give its respective output in following three classes

-Damaged part

- Undamaged part

-Missing part

## RESULTS

User will upload a car image or images and number plate of car, and we extract car registration number in text form using Googles Tesseract OCR. After Login output of prediction in three classes - After Login output of prediction in three classes -Damaged part, Undamaged part, Missing part, User will select the correct number among 3 outputs which our system generated., And then This registration number will be passed to RTO, and following fields will be fetched from RTO, Output from RTOWe are calculating cost for the parts which are damaged. As each make and model of the car have different costs, we can use RTOs fetched information to specify make and model of the car, and fetch respective models' costs from database And then report of estimation in pdf format will be generated.

## CONCLUSION:

This paper has generally discussed the design and implementation of damage assessment for car insurance (DACI) by developing deep learning car damage classification model on website development platform where user will upload image or images of damaged car with help of phone's camera. then according to damage calculation, the total cost of car will be displayed in a report format. This system is tested over a wide range of images yielding high accuracy rate

## Title 3: Vehicle Part Damage Analysis Platform for Autoinsurance Application

## Author:

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## ABSTRACT:

An automatic vehicle damage detection platform can increase the market value of car insurance. In this paper, we present a damage vehicle part detection platform, called Intelligent Vehicle Accident Analysis (IVAA), which provides an arti cial intelligence as a service (AIaaS). It helps automatically assessvehicle parts' damage and severity level. There are four main elements in the service system which support four stakeholders: insurance experts, data scientists,operators, and  eld employees. Insurance experts utilize the data labeling tool to label damaged parts of a vehicle in a given image in a training data building process. Data scientists iterate to the deep learning model building process for continuous model updates. Operators monitor the visualization system for daily statistics related to the number of accidents based on locations. Field employees use LINE O cial integration to take photos of damaged vehicles at accident sites and retrieve repair estimations. We deploy the CapsNet model to localize the damage region and classify it into 5

damage levels for a vehicle part. The accuracyof the localization is 91.53 % and the accuracy of the classi cation is 98.47%.IVAA provides near real-time inference. The usability evaluation of the proposed

platform is separated into two aspects. First, it got 4.69 of 5.0 scores in a usability test of the application module. Second, it got 4.66 of 5.0 scores in a usability test of the intelligence module.

## INTRODUCTION:

The role of auto-insurance companies is to provide services to their customers supporting the claims pro�cess. Providing fast service in the �eld and fast dam�age repair quotations are the keys success to satisfy their customers. The traditional approach may take 15 minutes to an hour of waiting for a user to get the repair quotation from the insurance experts at the company where the car must be seen before the quotation can be done. Field employees spend a lot of time to inspect the vehicle at an accident site in the traditional claim process.

The traditional claiming process begins with anappraisal where either the insurance company will send someone out to the customer car to evaluate the damage, or the customer brings the car to the company or a registered body shop. This is usually a time consuming process. With the advancement of articial intelligence, the traditional claim processing time can be shorted while the customer satisfaction is increased. The assistance of articial intelligence can allow the eld employee to process the claim automatically and can complete the quotation in minutes. Our proposed service system can be integrated with the existing system.

Artificial intelligence is an advanced technology that emphasizes creation of intelligent machines that work and react like humans. The core areas of artificial intelligence are knowledge, reasoning, problem solving, perception, learning, and the ability to manipulate objects. The deep learning technique is an effective methodology to build an intelligent agent. The area is quite mature for recognition tasks. In this paper, we provide a platform to help auto�mate the vehicle claims process. The platform con�tains four elements which involve the four stakeholders: field employees, insurance experts, operators,and data scientists. Line chatbot allows the images of the car damages to be submitted through the system for damage assessment and claim filing. This enables the field employees to do less work on sites. The claimfiling and images are recorded through the central database. The web application allows the operators to perform visualization and analyze the claim status and accident cases. The data labeling tool aids the insurance experts to annotate the vehicle parts and damage levels. The annotated data is saved in the database and used for training to regularly update the damage classification model. Finally, the deep learning APIs allow the pipeline of maintaining the up-to-date model and gateway to interact with the LINE chat bot. The four elements together enable an auto insurance company to automate the claims handling process using artificial intelligence The rest of this paper is organized as follows. Section 2 describes related research work about artificial intelligence as a service and image processing. Section 3 explains the system design of our system. Section 4 presents the implementation of each element. Section 5 evaluates the accuracy of the damage classification model and user satisfaction. Section 6 presents the conclusion and future work of this research.

## RELATED WORK:

Artificial intelligence has greatly improved the effectiveness of both manufacturing and service systems. Recent commercial systems, such as IBM Watson, have been established to provide cloud services for facilitating creating AI and machine learning applications. Watson is able to report the possible defects on the car and show the types of checking performed. The system contains three elements: Watson Visual recognition, a web server, and a mobile application[1]. The Watson Visual recognition partutilizes the recognition services from IBM clouds for damage classification. Figure 1 presents an example of using the application that analyzes the car damage from input photos. Another example is the car damage detective software which is an open source project on Githubby Neokt[2]. It analyzes the damaged vehicle parts with a convolutional neural network. The recognition model was trained based on 3 models and uses images scraped from Google for training. Model 1 is used to classify whether the vehicle is damaged or not. Model 2 is to classify location of the damage into 3 classes (front, rear, side). Model 3 classifies the severity of the damage into 3 levels. The location accuracy and detection accuracy are around 79% and 71% respectively

## METHODOLOGY:

This section describes our Intelligent Vehicle Accident Analysis system platform (IVAA). We divide the section into three parts:

(1) system elements,

(2) system software architecture,

(3) deep learning model

## System Elements:

Figure 3 displays four stakeholders of the IVAA system: insurance experts, data scientists, operators, and field employees. The platform has four tools for these four users: a data labeling tool for insurance experts, deep learning APIs for data scientists,a web monitoring application for operators, and a LINE chatbot to interact with the back-end server for fieldemployees.Data labeling is one of the time consuming tasks.The traditional labeling software such as LabelImg [12] and Imglab [13] works as an offline application. We integrated the data labeling tool and provided a web interface where the users can collaboratively work on the labeling task. The labeling tool returns a downloadable JSON file for the user for future use. VueJS is used as a front end framework with a Rest API server. The labeling tool is useful for adding more information to the labeled image of damage for future retraining. Deep learning APIs are gateways which are specifically designed for data scientists and developers to train and make use of the model in applications. For training, the API returns the model identification(model ID) to the user as a link for the model deployment. For testing, the API returns with the list of damaged parts and their damage levels on the vehicle after an accident along with the confidence levels. For the operators, the web monitoring application shows historical data that contains the number of cases, the number of processed images, and the number of days that system has operated. Graphical visualization on the system contains heat map visualization which represents the frequency of accidents by location and dates. For field employees, we provide the LINE chat bot. The employee sends the damaged car images and the chat bot gives the resulting car model and price table images, along with the list of body shop locations.

Note that we adopt LINE as a user interface because the requirement of the interface in the proposed system is only to receive the damaged vehicle image and return the result, and the LINE application is able to provide these features. Furthermore, we consider the installation of the application due to the fact that theLINE application can be installed on both iOS and Android

The information details of an accident case, such as the customer ID, the accident location, and the damaged car images, are sent to the chatbot. In the backend, the deep learning testing API is executed to recognize the damaged parts and classify their damage levels from the submitted photos. The relevant information about the customer and accident are also recorded in the main database

## System Software Architecture

Our services can be deployed as a private cloud system with the hardware specification in Table 1.The private server is used for modeling, the model deployment website, and database hosting.the software stack of the system. OpenStack is used for computational resource management such as memory, CPU, network and other resources to provide for each of the specified tasks in the container. The visualized resource monitoring part is divided into 2 sections. The first section uses Grafana to monitor resources on the private cloud via OpenStack. In the second section, Sahara is used to monitor resources on the private cloud directly. Kubernetes provides scaling computational resources on each docker container. Docker engine is used to We keep each trained model's replica on a single GPU. It turns out that for the memory footprint of layers with large activation, the size is disproportionate to the amount of GPU memory. By omitting the batch-normalization on top of those layers, we were able to increase the overall number of Inception blocks substantially. We hope that with better utilization of computing resources, making this trade-off will become unnecessary

## EVALUATION

We conducted an evaluation that compared the three models: IVAA classification model, template matching, and object detection, on the selected data sets. We compared our model with two different techniques using the accuracy of detecting the damaged vehicle parts without identifying the damage levels.First, template matching is a technique in digital image processing for finding small parts of an image which matches a template image. The object detection algorithm typically uses extracted features and learning algorithms to recognize instances of an object category.We applied template matching to match the damaged vehicle part with the input image.

But it is not accurate since the template matching can match only damaged vehicle parts that have been seen before. Template matching was implemented using the OpenCV library based on 1. Secondly, we applied object detection to detect the damaged vehicle parts.The object detection library obtained from Tensorflow employs Faster R-CNN. Faster R-CNN is an object detection algorithm that is similar to R-CNN.This algorithm utilises the Region Proposal Network (RPN) that shares full-image convolutional features with the detection network in a more cost-effective manner than R-CNN and Fast R-CNN.The accuracy of finding the car parts with various algorithms is measured using the Toyota Camry image set available on 2. The data set is gathered fromTraffic Safety Administration, and Thai General Insurance Association. The data set contains 1,624 images.

We divided 80% for training and 20% for testing. Moreover, we apply CapsNet to increase model accuracy by increasing input data dimensions for the damaged vehicles. Our IVAA network provided accuracy of up to 98.47% as shown in Figure 14. IVAA has greater accuracy than using the template matching approach (93.58%). The object detection approach of traditional computer vision techniques explores multiple paths where the algorithm is simplified, yet it can achieve higher accuracy but with less computational cost (91.53%). In the chatbot application,we set the threshold for bounding box detection and severe classification to 98.47%. For our case, Intersection over under (IoU) for our proposed system is93.28%.Figure 15 presents the inference time as the number of images grows until 20 images on our private cloud. This shows service capability when lots of inference requests come in. The average inference time per image is 12.12 seconds on our private cloud. the confusion matrix when using the IVAA network to classify the parts of vehicles. It shows that our model can detect the damaged vehicle parts very accurately. The data set and the comparison code of the tested car are available 3.

In addition,we provide the script to train the pre-trained neural network model for new images in our project’s gitlab repository.We also evaluated our users’s satisfaction with our applications in two aspects: application usage and intelligence module. For application aspects, A questionnaire was used. It measures system satisfaction in two modules: (1) application module test in Table. 3, and (2) intelligence module test in Table. 4.For the application aspect, there are usability, reliability, security, interface, and availability [14]. Example questions include: “What is your satisfaction for the application interface?”, “What is your satisfaction for the prediction speed and accuracy?”, etc. Table 3 shows the usability test results of the application module in the proposed system. The usability results show the capacity of a system to provide a condition for the users to perform the task safely. The proposed system achieves 4.93/5 for usability. For the reliability aspect, we obtain 4.76/5. For the security score, we obtain 4.56/5. For the ease of interface, we obtain 4.66/5. For availability, the score is 4.56/5. The average overall score is 4.69/5.Table 4 shows the usability test of the intelligence module in the proposed system. The proposed system yields 4.76/5 for the satisfaction score of prediction speed. The prediction speed is defined as the time from sending the images until receiving the result. The prediction accuracy score is 4.56/5 This shows the measurement of the user satisfaction with the prediction’s accuracy based on human observation. The prediction’s expectation score is 4.60/5. The satisfaction scores for input data and with the output data format are 4.53/5 and 4.83/5 respectively. The average overall score is 4.66/5 for the whole intelligence module.

The aspects are prediction speed, accuracy,expectation satisfiability, input format satisfiability , and output format satisfiability.We surveyed the opinions from 30 general users. The average score for each aspect is shown. The score is out of 5. The average overall score is 4.69/5 for the application side and 4.66/5 for the intelligence module. There are 93.3% of users who highly recom the system to their friends or companies. Our IVVA system provides an end-to-end platform for facilitating auto-insurance damage assessment and accident reporting. From the customer side,he/she can use the chatbot to report the accident and ask for damage assessment. From the insurance company aspect, the company can use the web application for monitoring accident cases. For the data scientists, the platform provides the tools for image labeling, APIs to retrain the model, and model deployment. The system implementation is based on Docker, which is convenient to deploy

## CONCLUSION

The Intelligent Vehicle Accident Analysis System(IVAA) is an artificial intelligence platform as a service. It provides an end-to-end solution for an autoinsurance company. It consists of four modules: the first module is a data labeling (for insurance experts),the second module is deep learning API for data scientists, the third module is the web monitoring application for the operators, and the fourth module is LINE official integration for field employees. Other open source solutions usually offer only damage classification feature using offline photos. The docker container is used for easy deployment. The current deep learning model used is CapsNet, which can predict correctly up to 98.47 % when testing on the proposed Toyota Camry data set. The average image inference time is 13.12 seconds. We evaluated user satisfaction for our application and intelligence modules aspects. Scores were 4.69/5 and 4.66/5 respectively.Future work includes integrating our proposed system with the driver's application and automating the whole process of retraining when adding more images using scheduling. A database of body shops is also being collected.