LITERATURE PROJECT ON INTELLIGENT VEHICLE DAMAGE ASSESMENT AND COST ESTIMATOR FOR INSURANCE COMPANY

LITERATURE SURVEY

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 articial intelligence as a service (AIaaS). It helps automatically assess vehicle 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 Ocial 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 accuracy of the localization is 91.53 % and the accuracy of the classication 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 process. Providing fast service in the eld and fast damage 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 an appraisal 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 automate the vehicle claims process. The platform contains 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 claim filing 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 chatbot. The four elements together enable an autoinsurance 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 part utilizes 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 Github by 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.

Using deep learning is a popular approach for object classification and detection tasks. The convolutional neural network (CNN) is the popular model for these tasks. Convolutional neural networks use translated replicas of learned feature detectors. This allows them to translate knowledge about good weight values acquired at one position in an image to other positions. To build high-quality graph embeddings, it is important to not only detect the presence of different structures around each node but also preserve their detailed properties such as position, direction, connection, etc. However, encoding these properties' information in the form of scalar values means activating elements in a vector one-by-one, which is exponentially less efficient than encoding them with distributed representations.

For the object detection task, a CNN is useful for both location detection and classification at the same time. The most commonly used network is Faster Region-based Convolutional Neural Networks (R-CNN) [7]. Faster R-CNN is actually an improved version of R-CNN (Region-based Convolutional Neural Networks) [8]. The algorithm of this network breaks down into 2 separate stages. In the first stage, regions within the image that are likely to contain our object of interest (called ROI) are identified. In the second stage, a convolutional neural network is run on each proposed region and outputs the object category score and the corresponding bounding box coordinates that contain the object. The original version of R-CNN uses selective search to generate proposed regions for the first stage, then uses a pre-trained VGG-16 to extract features from the proposed region and feeds those features into SVM to generate the final predictions. Faster R-CNN is an improved version which runs faster and is more accurate. One of the major modifications of Faster R-CNN is to use a CNN to generate the object proposals as opposed to selective search in the prior version [9]. This layer is called the Region Proposal Network (RPN). RPN first uses a base network (e.g. VGG-16, ResNet-101, etc.) to extract features (more precisely, feature maps) from the image. It then partitions the feature maps into multiple square tiles and slides a small network across each tile successively. The small network assigns a set of object confidence scores and bounding box coordinates to each tile location. The RPN is designed to be trained end-to-end in a fully convolutional manner.

A capsule is a small cluster of neurons that learns to determine the exact object in a given image and produces a vector whose length indicates the estimated probability that the object is present and whose orientation encodes the posture characteristics of the object [11]. If the object is moved slightly, the capsule will produce a vector with almost the same length but a slightly different direction. Consequently, the capsules have a similar composition.

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, and (3) deep learning model.

SYSTEM ELEMENTS

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 field employees. 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.

DEEP LEARNING MODEL

For the damage recognition, we utilize the capsule neural networks (CapsNet) to locate and classify levels of damage in the vehicle photos. The confidence level is returned from the deep learning API. The process of utilizing CapsNet is shown in Figure 6. There are six main steps in the figure. The input image is resized to 28× 28. In (1), the damaged part is obtained from the input photo by cropping into the size 9 × 9 which is used as an input to the next step. The part is reconstructed by minimizing the squared difference between the reconstructed one and the input. Next, in (3), the two convolutional layers are used to reshape from 32 primary capsules to 6 × 6 × 8. In (4), these primary capsules are fed into higher layer capsules. A total of 5 capsules with 16 dimensions each and the margin loss are calculated with these higher layer capsules to predict the class probability. In (5), the model computes the location of the damaged vehicle part. In (6), softmax is used to compute the damage level of the damaged vehicleFor the damage recognition, we utilize the capsule neural networks (CapsNet) to locate and classify levels of damage in the vehicle photos. The confidence level is returned from the deep learning API. The process of utilizing CapsNet is shown in Figure 6. There are six main steps in the figure. The input image is resized to 28× 28. In (1), the damaged part is obtained from the input photo by cropping into the size 9 × 9 which is used as an input to the next step. The part is reconstructed by minimizing the squared difference between the reconstructed one and the input. Next, in (3), the two convolutional layers are used to reshape from 32 primary capsules to 6 × 6 × 8. In (4), these primary capsules are fed into higher layer capsules. A total of 5 capsules with 16 dimensions each and the margin loss are calculated with these higher layer capsules to predict the class probability. In (5), the model computes the location of the damaged vehicle part. In (6), softmax is used to compute the damage level of the damaged vehicle

WEB APPLICATION

The user must login through the web application first. Figure 9a shows the dashboard on our system. Dashboard is a data visualization tool that allows all users to understand and analyze what is going on. The dashboard provides an objective view of performance metrics and serves as an effective foundation for further analysis. Figure 9b is a heat map showing the volume of accident events by location. Fading color is based on the density of accident cases at the location.

An accident case can be inserted via the case insertion page. For each accident case, the user is required to specify the case identification number, customer identification number, accident location, and to upload the photo of the damaged vehicle involved in an accident. A drag and drop approach is provided for uploading the photo with more convenience. The submitted case can be reviewed for approval and the system shows the case's information in Figure 9c. The case information page visualizes the damage level on four views of the vehicle. Moreover, it indicates the clarification of repaired price based on the damage level. Furthermore, the operator can also look up all historical accident cases. The search can be done by case ID, customer ID, and accident date. The detail button is used to show the detailed information.

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 from https://carscales.com.au, the National Highway Traffic 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 is

93.28%.

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.