

Image recognition in auto damage claim process

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Abstract

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| Through interest in applicable technology in business and desire to close the gap | | | | | | |
| between business and technical view, the author attempted to take image recognition | | | | | | |
| and insurance as a combination. The primary goal of this thesis is to examine how | | | | | | |
| the image recognition revolutionize the damage claim process in auto insurance. | | | | | | |
| Due to the nature of introductory stage of the technology, there are a few public | | | | | | |
| comprehensive documents and service providers. Theoretical studies are conducted | | | | | | |
| through the reliable market research agencies, and technical articles regarding the | | | | | | |
| topic. The data analysis is based on conducted interviews with auto inspection | | | | | | |
| service providers with semi-structured questionnaire (Appendix 2) and also published | | | | | | |
| speeches and article from the 4 target companies. | | | | | | |
| As the result, the image recognition is the new competitive edge to insurance carrier | | | | | | |
| in auto insurance. The concept of extracting and making sense of data from images | | | | | | |
| provided has brought main impacts: timely and accurate information, streamlined | | | | | | |
| process, high processing capacity. As a result, the technology enables shorter | | | | | | |
| processing time, higher accuracy in detection and estimation, thus less human | | | | | | |
| intervention, and image fraud detection. | | | | | | |
| | | | | | | |

Keywords: Image recognition, Computer vision, Auto insurance, Car Insurance, Damage Claim, Insurtech, Insurance technology.

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Appendix 1 Interview invitation letter

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1 Introduction

1.1 Research background

The current situation of car insurance industry has a huge waste on claims' leakage. Claim leakage is the overpay in claim payment due to visual inspection (IRJET 2020). And according to the research of McKinsey (2018), claims processing in 2030 remains a primary function of insurance carriers but head count associated with manual claims is reduced by 70-90% compared with 2018 levels. Therefore, the urgency for claim automation is rising in all aspects of insurance.

The recent application of image recognition appears as a disruptively automative solution in traditional claim process, which is highly competitive on intelligent data extraction, personalization and fraud detection as the latest trends according to Forbes (2019). Additionally, the advancement of AI and machine vision, the automated process from raw images to the claims'amount through digital solutions are enabled with less dependence on manual adjusters (Insurance CIO Outlook 2020).

1.2 Concept and delimitations

Image recognition, or computer vision, is the machine or computer's ability to detect an object, a feature or an useful information from an image or a sequence of images, such as video.

Auto insurance, according to insurance information institution, is the agreement between the insurance company and its customer the protect him or her against financial loss during the event of accident or theft. The auto insurance provides the coverage for: property, liabilities and medical.

However, the purpose of this thesis is to cover the damage claim, specializing in property coverage of auto insurance, as the most growing area of insurance. The other liabilities and medical expenses would be excluded. Additionally, to ensure the alignment of claim processes, the thesis examines cases that data as images are

collected instantly from the policyholder's locations at their most convenience. Thus, the possibilities of services that transport damaged vehicles to the place of inspection are excluded from the research.

1.3 Research objectives and questions

As mentioned previously that the image recognition is transforming the industry. Property claim process is depending mostly on people, from inputting and evaluating the data from damages, which is time-consuming and causing errors. With the introduction of image recognition, the process is facilitated with lower processing time and higher accuracy. Focusing on one of the areas with the highest impacts of recognition and impressive growth, the thesis will cover the assessment of auto accidental damages in insurance. Hence, the research objective is to familarize with the concept of image recognition and its possibilities in facilitating the claim process of accidental damages in Insurance industry.

Thus, the foremost research question is how does image recognition revolutionize damage claim process in auto insurance. In order to give a comprehensive answer to the big question, there are supporting subquestions to be addressed within the area of image recognition and auto claim in the relativeness to the traditional method:

- What is image recognition and its mechanism?
- What values does image recognition contribute?
- What is key to success and future outlook of image recognition?

2 Image recognition

As in image recognition, on the object-level types, there are seven popular possibilities or models according to the Claim Genius (2020) including

- Classifying objects specifies the broad category of the object in the image.
- Identifying object recognizes the type of the object in the image.
- Verifying object confirms whether the object exists in the image.
- Detecting object locates where a certain object is in the image.
- Object landmark detection presents the key points of the object.
- Segmentation of the objects determines the pixels that belong to the object.
- Object recognition: that names the objects are in the image.

Each of the above possible uses are applied in a certain areas of business processes. Some of the procedures will require the combination of a few above methods in order to maximize the functionality.

In order to provide more insights to the image recognition process and mechanism, according to the Society of Actuaries (2018), the figure 1 illustrates the step by step to generate an application from the set of visual data gathered:

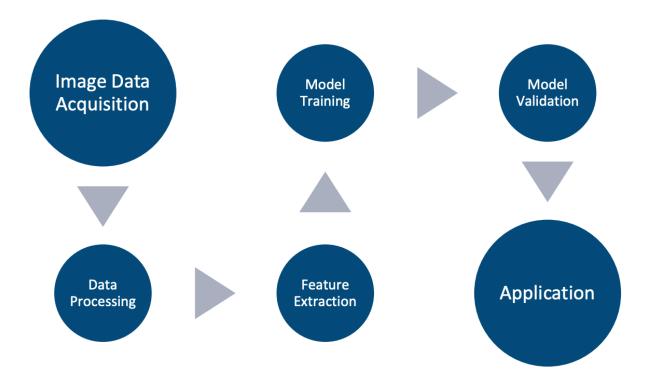


Figure 1 Image recognition process (Society of Actuaries 2018)

Though the usual process of image recognition application contains various steps of complexity, the overview is similar to traditional statistical analysis. From the figure 1, the flow of data is transparent from collecting with the aid of specialized popularly camera, drone or satellite. The images collected will be passed to processing, which renders data into smaller size, little noise and higher contrast for better input. Features, including basics of the images such as lines, intersections, borders, shapes and characters may be extracted from images. The input will be utilized for model training in order to link the image data with interested outcomes such as the object type and behaviors. The model is later refined and validated to ensure its predictability and satisfactory outcome. Certain measures and standards would be defined by each case to determine its practical application. (Society of Actuaries 2018.)

2.1 Image data acquisition

The main aim of image acquisition is to transform the data from the real world or optical images into the array of numerical data to be manipulated on a computer before processing (Mishra & Kumar 2017).

Image Acquisition is achieved by suitabe camera which are various for certain applications. There are x ray images, Infra Red images or normal ones that will require specialized cameras which are sensitive to these rays and the visual spectrum.

In the concept of insurance, images could be taken from the phone camera, CCTV camera and other convenient camera-installed facilities. The quality of images during insurance inspection need to be met before extracting reliable data.

According to the article of Mishra & Kumar (2017), success of image acquisition depends purely on Hardware Process, that converts the reflected light from the object into electrons.

2.2 Data processing

Society of Actuaries (2018) states that when the images are received, the very first step is to transform the image into the form that the computer could comprehend, which are numbers. A picture is technically made from pixels, the basic unit in digital imaging. Each pixel is defined by a color, which is specified by a color imaging system. The RGB coloring system is believed to be most popular and define any color in the combination of three dimensions: red, green and blue with a certain code of mixture. An easy example is shown below as the green color is coded as (0,128,0) and white color as (0,0,0), with the sequential contribution of red, green and blue.

| | (0,0,0) | (0,128,0) | (0,0,0) |
|---|-----------|-----------|-----------|
| = | (0,128,0) | (0,128,0) | (0,128,0) |
| | (0,0,0) | (0,128,0) | (0,0,0) |

Figure 2 Image data representation (Society of Actuaries 2018)

Additionally, besides RGB coloring system, there are other lights that can not be seen by human eyes or captured by normal cameras such as infared, x ray, etc. Image recognition tasks are relatively similar to quantitative analysis when it deals with mostly numbers encoded from the pixels. However, the volume is usually much larger and the input data need to be processed into meaning features for a statistical model. The image processing section will generally cover the main idea from data transformation, augmentation, feature extraction and autoencoders. The final result of this step is to provide applicable features for the model training.



Figure 3 Original image (Hype 2016)

Data transformation is the process of altering the original images for certain purposes. When the data image is too large and demanding large computing capacity. While colors are made necessary for the analysis of human, the computers do not see colors as important as relative brightness of pixels. The solution could be transforming the original ones in RGB scale into gray scale that could reduce the image volume drastically. Another solution could be downsizing the original image to lower resolution. This transformation could reduce not only the storage requirement but also increase the strength of computer processing due to less details, which leads to improved computing speed and administrative burden.



Figure 5 Greyscale image (adapted from Hype 2016)



Figure 4 Compressed image (adapted from Hype 2016)

In other cases image could be blurred by adjusting the pixels according to the values of its neighbors. The images could also be sharpened to enhance the edges' contrast. With any type of transformation may be applied, the images are meant for improving model input and the accuracy of image recognition can not be compromised.



Figure 7 Blurred image (adapted from Hype 2016)



Figure 6 Sharpened image (adapted from Hype 2016)

Beside changing the content, data augmentation could also be possible before entering the model. Usual augmentations include flipping, rotating, shifting, cropping, and brightening. The purpose of augmentation is to provide the material with adjustments as additional training examples to ensure the model's efficiency



Flipped





Rotated



Cropped

Figure 8 Image augmentation (adapted from Hype 2016)

Moving to feature extraction, this could be done by using descriptive statistics such as the mean, the vitality, skewness, kurtosis, and percentiles of the pixels as the data feeding to the model. For a more advanced method, feature can be extracted by measuring the changes from pixels. By detecting the edges, the machine will get an idea of patterns needed to generate meaningful recognitions. (Society of Actuaries 2018.)

2.3 Model training

During this step, the data collected and processed are used as the input to train the model in order to retrieve the meaningful information. Mostly successful image

recognitions models are developed from convolutional neural network (CNNs). Through image recognition models, there are many similarities to the traditional underwriting models. By determining the relativeness of key points from the image and its connection, Image recognition model could extract and learn from the fed data for further improvement. (Society of Actuaries 2018.)

Neural networks

Neural networks are the tools of machine learning. Within the networks, the computer learns to perform a certain purpose by analyzing examples as a part of training process. The examples in this context are images for recognition purposes. (MIT 2017.)

Rather than statistical models, neural networks are believed to be more important in actuarial analysis. In these statistical models, the relationships are usually pre-defined as linear or non-linear equations. Instead of depending the image content on a single pixel's role or weight, image recognition utilizes the relative locations and contrasts, as more important information.

Convolutional neural network (CNNs)

Convolutional Neural Networks (CNNs) are advancedly specifying a certain areas of interest in a certain image instead of spreading the analysis over the whole as Fully Connected Neural Network. CNNs are now widely applied for model training in image recognition by reflecting the local connectivity of pixels, imitating the human subconsious mind while looking for objects and clues within a big picture. These small important areas are called as receptive fields. Receptive fields help reduction in computing requirements and higher efficiency from only informative specifics. (Society of Actuaries 2018.)

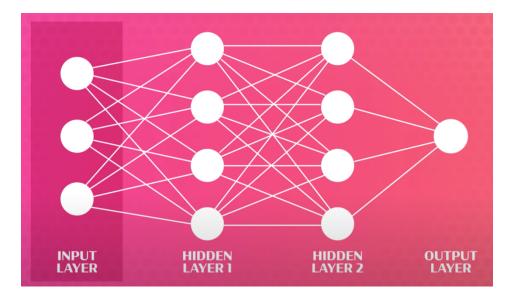


Figure 8 Neural networks (Crash course 2019)

According to Crash course (2019), The figure 9 is a simple and classic illustration of convolutional neural networks. The input layer is the place where neural networks would receive the data in form of numbers as described during the data processing phase. There are layers starting from input layer, where the data are transferred from previous step, and hidden layers. The circles neurons are connected between one another. Each of them sends the signals to all the next neurons, in the next layer within the network for analysis.

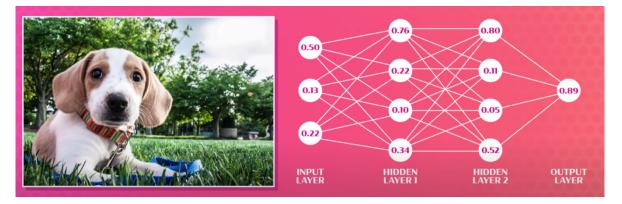


Figure 9 Model training sample (Crashcourse 2019)

This is the sample of image recognition to define whether the left side image is a dog. For the white circles within the figure 9, each represents a single feature, extracted from the given image. Each circle contains a feature number, extracting mostly from the image's edges such as the nose, the mouth and the ears. From the values at the input layer, the hidden layer 1 would consider the relativeness of these such as the distance and symetry between two nostrils, the shape of the mouth and ears and result in numerical figures. During the process between hidden layers, the computer attempts to define a certain integral components of a dog in order to define the object as a whole by considering pixels, its weight and relativeness. The final layer would result in a figure raging from zero to one which will specify how many percent of accuracy or similarity of the picture with a dog. (Crashcourse 2019.)

Activation function and Pooling

Within the same study from Society of Actuaries (2018), the activation function is applied to the neuron's value before being sent to the neuron in the next layer. Depending on the value, the next neuron would be either activated or not. The range of value are flexible raging from negative infinity to positive infinity, depending on the type of output. The activation functions plays like a measurement method to make the values manageable

According to Society of Actuaries (2018), Pooling layers, as illustrated in figure 11, is down sampling that merge a few pixels into one. With the purpose to retain the highly informative pieces, pooling method could reduce calculation and data dimensions.

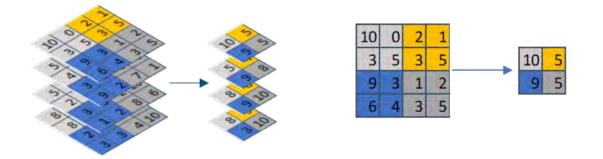


Figure 11 Max pooling (Society of Actuaries 2018)

The above process (figure 11) demonstrates the max pooling, which is popular in image recognition. The idea is to keep only the maximum values from the subsets, same colored squares to be transferred to the next step. From 4x4 matrix, max pooling reduces into 2x2 matrix till the final stage. There are other pooling methods worth mentioning such as average pooling by extracting the average value or stochastic pooling which uses the random element from the set. (Society of Actuaries 2018.)

2.4 Validation

After the period of continuous training, the model has learned sufficient information for performing the task. Validation step is conducted to test the accuracy of information the model could provide. The accuracy of the model depends solely on the dataset. The variety of data set in terms of angels, brightness, background and other variables, will contribute to the accuracy rate. On another hand, while the data is not sufficient, the accuracy of application also fail to perform. (Society of Actuaries 2018.)

3 Auto insurance applications

3.1 General evolution

In general, the application of image recognition would increase the proceeding of auto damage claim by reducing the steps and the processing time thanks to the technology. The figure 12 is the structured process of traditional claim:



Figure 12 Traditional damage claim process (Altoros 2020)

For the traditional method, the claim process will undergo total six steps to final insurance payment. The very first one is claim submission with images together with the receipt submission, showing the costs of repair. All the information is manually transferred into the system for analysis and records. The claim would be assessed by the responsible employees with previous experiences of cases. The approval decision would be determined afterwards and proceed with possible insurance payment. Though the process seems structured and logical, the involvement of human element is still crucial and foremost. By earning the experience from previous image cases, the employees could be more prompt to solve the incoming cases with more accuracy. However, processing a huge data of image data and repair cost estimation would be the disadvantage compared to the computer and its mechanism. (Altoros 2020.)



Figure 13 Applied image recognition in damage claim process (Altoros 2020)

For the second pathway of image recognition as in figure 13, the procedures are reduced to only four. The new process shares the similarity in the first and final steps. During the middle, there are simplified two steps which are performed by computer vision. The first one is auto check and cost estimation in which the information are extracted from submitted images for processing. The parts, other than auto, were guided by machine learning to streamline the claim until payment decision. With the variation from insurance providers, there are assisted services and self-services within the auto insurance market, that are classified by whether there is the involvement of insurance agent. In the assisted services, the insurer would connect with the customer and share the cause and severity of the damages, which will provide the most reliable and images as required. On another hand, the self-services rely completely on the submitted images which will lower the processing time to payment decision. (Altoros 2020.)

3.2 Information extraction

Continuing the advantages of image recognition in details, the below subsections will clarify how image recognition benefit the auto insurance industry in terms of technical aspect. Each of the functionality would play a role in the claim process, from retrieving auto basic information, detecting the damaged components and its extent.

Auto basic information

According to Databricks (2020), starting from 2012, the Deep Learning Revolution enabled image recognition to classify car images into specific car models with steps described in the figure 14. The car models as basic information set the standard cost estimation of repair and replacement due to the noticeable difference in pricing. Unlike human mind while familiarizing with definition of a car, the computer vision could study right from the images of car, which are fed in huge amount into the model. Through visual data, the computer could see the patterns and classify images with almost human-level accuracy.

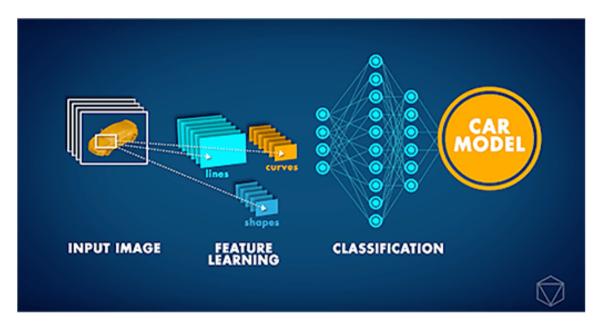


Figure 14 Neural network for car model classification (Databricks 2020)

The neural network were retrieving 16,000 images of cars of 196 different models from the Standford Cars Dataset, which is one of the most comprehensive public datasets. Through specific features such as lines, curves and shapes, and many more, the model had learned through time and increased its accuracy in successfully classifying different models. (Databricks 2020.)

The locations of damaged components

The car images are processed within the neural network. The neutral network in this phase would be trained from Transfer Learning and Object Detection Algorithms. Transfer Learning is a machine learning method where a model is developed for one task and reused for a new but related task (Hussain et al. 2018). Object detection, as mentioned earlier, is the act of localizing a specific object in the image. In most cases, the damages would be manually proceeded for evaluation of damages (Towards data science 2019). However, the latest version of image recognition model is able to detect the damage location on the car body and estimate the severity of damages with little human intervention.

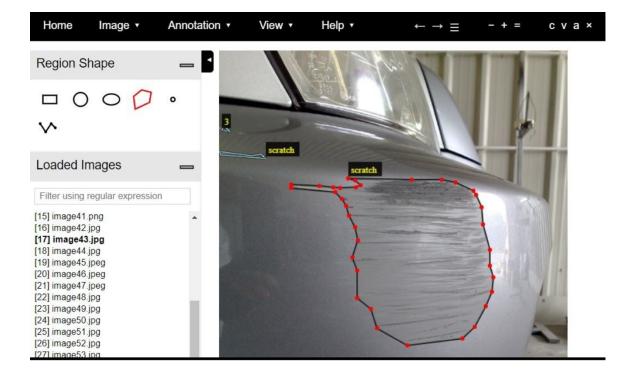


Figure 15 Sample of damaged component (Towards data science 2019)

The figure 15 has shown a vivid example of a Convolutional neutral network, especially VGG image Annotator (VIA). The author has submitted images and chosen the mask shape on the top left corner to mark the edges of the damaged part for training purposes. The case model later is input with more datasets including both images and annotations for training and validation purposes. The continuation of repetitive training would enhance the accuracy of the model.

| image ID: damage.image52.jpeg (1) C:/Users/Sourish/Mask_RCNN/custom/val\image52.jpeg | | | | | | | | | |
|--|--------|--------------------|------|------------|------|------------|-------|--|--|
| Processing 1 images | | | | | | | | | |
| image | shape: | (1024, 1024, 3) | min: | 0.00000 | max: | 255.00000 | uint8 | | |
| molded images | shape: | (1, 1024, 1024, 3) | min: | -123.70000 | max: | 141.10000 | | | |
| float64 | | | | | | | | | |
| image metas | shape: | (1, 14) | min: | 0.00000 | max: | 1024.00000 | int32 | | |
| anchors | shape: | (1, 261888, 4) | min: | -0.35390 | max: | 1.29134 | | | |
| float32 | | | | | | | | | |
| gt_class_id | shape: | (1,) | min: | 1.00000 | max: | 1.00000 | int32 | | |
| gt_bbox | shape: | (1, 4) | min: | 272.00000 | max: | 930.00000 | int32 | | |
| gt mask | shape: | (1024, 1024, 1) | min: | 0.00000 | max: | 1.00000 | bool | | |
| The car has:1 damages | | | | | | | | | |





Figure 16 Prediction result of sample case (Towards data science 2019)

The final phase as demonstrated in figure 16 is testing model predictability before application. The result was acceptable as it could mark the area of scratches on the hood of the auto and also quantify the severity extent of scratches. (Towards data science 2019.)

Fraud detection in submitted images

In the growth of technology, images are processed more by the computer vision in a large amount. Together with the trend, there is also the simultaneous rise of fraudulent claims in insurance as a deceptive act. The claims can be repeated for identical damages in order to deceive the system or people, which leads to the big loss to the insurance carrier.

The section would exemplify the solution by examining the case study "An Anti-fraud, System for Car Insurance Claim Based on Visual Evidence" from the University of Notre Dame (Li et al. 2018). In brief, the solution is about capturing the images from the dataset, originating from both internet popular searching engines and local public parking lots, with manual annotations and augmentation provided. From these databases, the model is trained by being fed the same car damage but taken in various contexts. The variables could be lightning, angels of capturing, surroundings, etc. The system, after successful training, would accomplish two main tasks: providing a real-time, accurate damage locations in the received images, and extract the feature to generate global and local deep features for anti-fraud matching, stored in the archives. (Li et al. 2018.)

Estimate the repair costs based on the type of damage recognised

In order to add more values in to the chain of image recognition, estimation of repair costs are predicted. Image recognition is able to collect the data, about whether it is a scratch or a dent, the size and shape of the damage, the car basic details, etc in order to determine whether it could be fixed or replaced. To predict the repair costs, the data source from the repair shops is utilized. According to Data Reply (2020), a statistical evaluation is made based on the earlier mentioned factors, refering from the similar car model from the database. Together with the real damage from photos, the model could finalize an overall cost estimate.

As the process of estimation involves various elements of the car images, from damages from particular angels, the vehicle basic details, combined with the insurance policy. Claim Genius (n.d) declares that its flagship estimation system could generate instant decisions on total loss and damage estimates after the customer upload the submitted images and videos through its app called Genius APP. The figure 17 is a thorough example on how the estimates are extracted from the image.

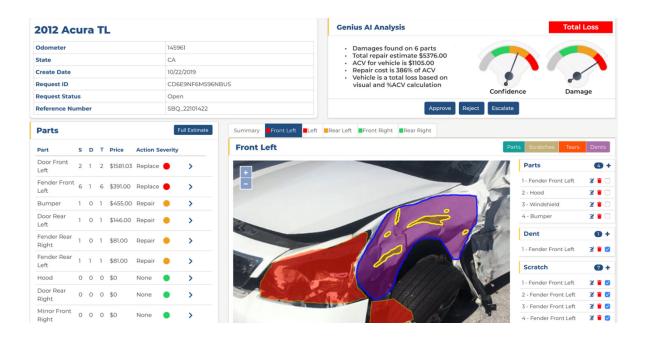


Figure 17 Thorough example of damage evaluation (Claim Genius n.d)

3.3 Business competence

With the integration of image recognition, the automation and digitalization has created huge positive impacts on the industry and the groups of interest .There are several advantages worth mentioning in terms of business.

In the collaboration of these add-in features, the overal customer satisfaction would be increased, which solves the excruciating problem in the auto insurance industry and create trustworthiness between parties. Besides, the insurance company would also benefit from firstly time and cost efficiency and employee's overall improvement, by excluding the mundane manual jobs.

Complete and real-time information

Image recognition provides the most clear data information from the very first inspection. The data about car images after being processed would be visible to all involved parties within a short period. The real time information would be highly consistent and followed during the claim flow, as well as recording purpose.

Tailored strategy repayment

Image recognition would also serve the customers better with tailored plan for repayment. The personalization of repayment would satisfy the customers' current financial status at the moment of accident. Separate auto parts would be proposed with specific repair. Thus, the repayment suggestions are favored and consented by the customers, insurers and repair shops.

Shortened processing time

The human force into the process would process the claim with longer time depending mostly on the personal experiences, amount of claims and complexity of cases. The reduction in dealing auto claim would be obvious thanks to the computer vision and its algorithmns. Thus, the efficiency is highly enhanced as well as general operations of all parties involved. The absence of car brings customers a lot of inconvenience during their daily commute. With the added value, the car could be faster sent back to the customers. The insurer would expect less of processing time.

Accurate damage evaluation

The damage evaluation is carefully asessed by the model of image recognition which will exclude the mistakes and intuitive factors which might occur during manual estimation. The damaged appliances would be evaluated and indicated by severe level with high confidence. As the model is tested and trained with images before application, the accuracy is verified and acceptable.

The accuracy in evaluation also determine whether the car is repairable, according to NS Insurance (2019). There are cases that the car is taken to the garage and decided as not repairable. With the assistance of image recognition, the computer owns a bigger data and careful inspection to define whether the car is repairable without the presence of the repair shop representative. Therefore, the decision can be made immediately at the accident spot, to whether paying the claim or repairing the vehicle. (NS Insurance 2019.)

Cost efficiency

The application of computer vision drastically reduce the cost of firstly the employee, handling claim processes and repair overpayment. The employee, on another hand would be released from the clerical, boring work and focus on other advanced ones. The repair shop database would be automatically updated together with the new cases. Therefore, the system could specify the trusted and economical shops with required and compatible auto appliances for tailor-made recommendations. Reduction in processing time is also an important indicator of cost efficiency in the whole operations.

Furthermore, in the case of policy adjustments, image recognition could reduce the insurance carrier's cost by virtually assess the images instead of sending the adjusters to the scene. The automated process would save the company unecessary expenditure and a decent amount of workforce.

Fraud-free and transparent information

Taking U.S as a case country, the FBI estimated that the cost of insurance fraud without health insurance is more than \$40 billion per year, resulting in cost of \$400 to \$700 per year for average U.S family. Thus, some states has classified the act as crime with penalties. The same study also estimate the increase of fraudulent claims paid between \$5.6 billion and \$7.7 billions, which was around \$1.5 billion higher than the similar figures in 2002. (Information insurance instutition 2002.)

The computer vision model would be the optimal tool for receiving and detecting the frauds in the submitted images. The fraud could happen while the images are submitted for several cases, false visual report, or any other frauds which are seen as inappropriate for claiming as mentioned earlier. (Towards data science 2020.)

The information after being filtered would be recorded and exchanged between the responsible parties including the insurer, customers and repair garage with complete transparency. (Deloitte 2020.)

Continuous learning model

As the model is the application of machine learning, the process of optimization is seemingly unstoppable. The more cases that the model handle, the more images are inserted for analysis and learning. With the on-going training through experiences and cases, the accuracy rate in claim's fraud detection, damage evaluation and other features could be expected to rise.

4 Key to success of image recognition

As image recognition is still a newly introduced term in the insurance industry, the success of this technology requires strategic and technical considerations. Most concerned issues could be listed as business added values and maintenance, data strategy, and customer privacy.

4.1 Resource allocation

From existing business and its current premises and infrastructures, there is a huge transformation into the image recognition-based solution. Thus, it requires certain factors to be clarified and approved by the responsible personnel before execution. The decision to implement image recognition technology and its values need the involvement and understanding of the C-level executives, the Board of CX management. Specifically, the insurance company needs to identify which parts of the business that the computer vision can bring the value and also the return on investment. Knowing the own needs, the lead of transformation could proceed with relevant solutions on the market. There are available end-to-end platforms implemented by external suppliers. The suppliers usually provide demos, proofs of concept, and pilot deployment. (TechSee 2019.)

Employing the technology means also a data team to deliver, maintain and refine customer's experiences. There are data engineers, data scientists, technologists, cloud computing specialists, CX designers as a whole team to enable and maintain the evolution.

4.2 Data strategy

In order to achieve the high rate of accuracy, the requirement for datasets is enormous for the purpose of training. In order for the visual assistant to properly identify the damage, the model must process around ten thousand of images of a single car in different lighting, angles, and positions (TechSee 2019). The images as data are not always stored for ready use. Hence, the establishment of databases are utterly time consuming and labor-intensive. The data sources can be acquired externally or collected from internal sources, depending on the tailored strategy.

4.3 Customers' privacy

Images contain a lot of information about not only the car but also other details. Privacy is believed to be a big concern. Visual data obtained from customer's property could include several matters of privacy and security. There are unwanted features that might appear within the images such as human faces, living environment, especially important identity-related details. The issue will cause the business to ensure detection and eradication of inappropriate details, in a massive amount.

5 Research conduction

This section will explain in details how the empirical data is conducted. Thus, it will firstly present the research methods and the reason for choosing. Further, the data collection methods together with questionnaire design are explained in details.

5.1 Research method

There are knowingly qualitative and quantitative research methods. The quantitative research method is the process of collecting data, with the use of structured questionnaire. The responses are predetermined with certain options. The quantitative involves a large amount of respondents and procedures to gather specific forms of data in order to generate a numerical result. The method is best suitable for measuring, ranking and identifying patterns. On another hand, qualitative way of collecting data means dealing with data by observational techniques or unstructured questioning such as interview. The qualitative method will manifest in-depth insights about the subject. Additionally, the background of the subject in qualitative research is the meaning from human factor. (Burns & Bush, 2010, p.235.)

Knowing the definition of two research methods and their features, the qualitative research method is chosen for this thesis as the purpose is to gain the in-depth insights about image recognition and in which aspects that it impacts the auto damage claim services.

5.2 Data collection

This section will specify the data types and how each type of data is collected for analysis by the thesis author.

Types of data

There are generally known two types of data: primary and secondary. Secondary data is defined as the information collected by other researchers. Sources can be published books, magazines, scientific research, journals, academic journals, or annual reports, etc (Burns & Bush, 2010, p.201). And primary data is the data originating from the researcher by using the first-hand collection tools such as interviews, questionnaires and other observation techniques instead of existing source. (Burns & Bush, 2010, p166.)

As the nature of image recognition in auto damage claim is still at the introductory stage into the market, there are a limited amount of service providers. To ensure the data and its reliability from the majority, this thesis will collect data from both primary and secondary data. The primary data is collected through interview. And the secondary data originates from company's official sources: websites, documents and authorized people's speeches.

Primary data collection

The most common method of qualitative research is interview. The interview enables researcher to obtain in-depth insights of interviewees regarding to the research topic (Burns & Bush, 2010, p.167). The main subject of this thesis is the revolution of image recognition in auto claim process, specifically its mechanism, added values, challenges and expected future. The interview method opens various perspectives on how different the technology has impacted the mentioned sector. According to Burns & Bush (2010), there are three different methods: structured, unstructured, and semistructured interviews. The structured interview is associated with a list of pre-defined questions, the unstructured interview contains the big and broad question, which is followed by an open and general discussion. The semi-interview is the mixture of two structured and unstructured interview. The semi-interview methods will guide the researchers with a set of questionnaire revolving the topic and it also allows agility for both sides to raise additional questions for further discussion resulting in valuable insights (Burns & Bush, 2010, p.176,177; Bryman & Bell 2007). The structured interview suits quantitative research while semi-structure and unstructured interview is well implemented in qualitative research (Saunders, Lewis & Thornhill 2009). This also strengthens the choice of research method in this empirical data collection.

After deciding the potential interviewees for the research, the interview proposals

were customized to backgrounds, ensuring the following content: the general template (Appendix 1) including the interviewer's self-introduction, research topic and invitation message, together with an attachment of pre-defined Interview questionnaire (Appendix 2).

There are four companies targeted for the interview including Claim genius, Ravin AI, Tractable and Claim Genius. These companies share the same market of image recognition in assessing damages during auto claim process. There were twelve people invited for the interview and two have accepted the interview eventually. The interviewees are approached through two main platforms: Linkedin and email. The invitations were followed by mutual agreement about date, time and digital platforms for interview conduction (Skype, Zoom, Video Call) when the interviewees consent to the proposal. Interviewees for this research are those from business development and product development teams, who capture the main impact of studied technology and its expected influences in the market. Below is the companies and interviewees, and also the sources of secondary collection companies:

Primary data collection includes

Rushabh Jain – Head of Business Development of Claim Genius

Eliron Ekstein – CEO & Co-founder of Ravin AI.

Secondary data collection includes

Speech of Andrien Cohen - Co-founder Tractable (Cohen 2019)

Speech of Robin Challand – Ageas UK Claims, Tractable's client (Challand 2019)

Speech of Julie Kheyfets, Head of North America of Tractable (Kheyfets 2019)

Online articles about Jas Maggu, CEO and founder of Galaxy.AI (Maggu 2018).

5.3 Questionnaire design

In the designing process of questionnaire, there are two main areas aligning with the theoretical parts that will be explored: systematic view and business view. The business view is highly emphasized as the nature of the study. All the questions are restricted in the discipline of auto damage claim as part of insurance carriers.

Image recognition mechanism

How you define the concept of image recognition and its difference from the traditional vehicle damage claim?

How briefly the data is collected, fed to the model and validated before application in vehicle damage claim?

Additional values

What values image recognition has added to the damage claim process?

How to measure the image recognition performance, in statistics? And how good they outperform the traditional method?

Key to success and future outlook

What are key to success between services provider of image recognition in auto damage claim.

What is the future outlooks of image recognition in damage claim process in auto damage claim.

5.4 Validity and Reliability

Validity is the factor that defines the possibility of the researcher to measurability of the research questions. The validity can be assessed the coherence and equivalence of the literature theories and empirical research. Reliability is the possibility of reproduction of similar results if the same research topic was conducted. The

reliability can be assessed by altering the non-topic factors such as time, authors and other parts related to the research. (Malhotra, Wills & Birks, 2012; Middleton, 2019.)

6 Research data analysis

This section includes the analysis of researcher on the data collected from both primary and secondary source to ensure the validity and reliability. The structure of analysis follows the framework of research questions, subquestions, questionnaire. Specifically, the analysis revolves around the auto damage claim, first exploring the necessity of image recognition, its contribution to the current process, and lastly the outlook of image recognition.

Generally, the companies researched are specializing in providing services regarding to the auto inspection. Though the auto inspection is widely applicable in car industries and its activities such as sales, share, vehicle delivery, auction & sales, and especially insurance as the biggest market size. Though, within this thesis analysis, the emphasis is on auto inspection in claim process within insurance industry.

6.1 Image recognition and its mechanism

As the whole world is evolving to the state of automation, the artifical intelligent brings lots of possibilities, that are worth discussing. Insurance industry is not an exception. The covid pandemic has caused the urgency for streamlining and virtualizing or even touchless experience for the sake of customers. Image recognition is a totally different concept of automating the auto claim process, which emulates the human's triaging process. These are specified above chronologically. The flow is applied in the analysis of the first question.

For the common agreement, thesis places its focus on the business view when addressing the issue. And the specific technology as the competitive edge is hardly disclosed only on the business to business practices instead of public understanding. Therefore, the details of how the images are processed, what models are applied, features extracted and other technical facets, specifically for company cases are decluttered from the analysis.

Image acquisition

Within the perspective of insurance, specifically auto damage claim, the image recognition starts with the series of photos the customer uploads regarding the car damaged following the accidents. According to Challand (2019), via the app in phone, the customers are guided of which photos to take. Tractable ensures that images are correctly collected and contain enough details to build a map estimate. In term of image quality, Maggu (2018) claimed that the system owns algorithms to detect the quality of an image and consider various factors like lightning, clarity glare, etc. in real-time as the user is moving their cellphone while taking images.

Another source of images applicable for analysis is standard CCTV cameras, which is ultilized by Ravin.AI beside the traditional smartphone's photos. The company ultilizes the frequency of cars passing through the camera-installed sites such as gas stations, parking lots, building entrances, garages, etc. The cameras collect the images with 360 degree view in a seamless and objective way and obviously, according to the users' permission. Due to the nature of mass captured photos and high dependency on the CCTV cameras, the there is a huge advantage for Ravin AI in the modern and already widely installed security cameras while it hinders the success in more private and less camera monitoring. Another bright side of this method is ensuring the sufficiency of photos required regardless of the customer's skills and ability to take professional photos. (Ekstein 2020.)

Model training and feature extraction

In order to process data and train the model for evaluating auto damages, millions of cases and photos are needed. Various data sources of photos could be ultilized in the process, mostly coming from the insurance carriers and partners (Jain 2020). Therefore, each service provider which is in charge of their own technology is partnered with an organization which contains a large database of damaged cars and their past evaluation. The very first images play crucial roles in building the technology and sharpen it to the applicable extent of precision. For the companies studied, Tractable is partnered with Ageas UK Claims, which is the insurance company holding a database of over five millions people in order to build the pilot (Challand 2019). Ravin Al collected data and build their pilot while being positioned in

the airports in London and later in the European and United States markets with Avis Budget Group which specializes in car rentals (Ekstein 2020). This is mutually beneficial practice that the model training process was conducted through the input of practical datas provided by businesses. The organizations, on another hand, are piloting the brand new technology which provides them with real time data for improved operations and potential future collaboration.

Feature extraction is deciding types of data are useful and for which purpose. In the common sense, according to Ekstein (2020), there are three common features including damage severity, damage location, and estimated costs. From the biggest overall of 360 degree view of the vehicle, the machine could detects the geometry in pixels to detect the abnomalies from the cars through images. Technically, the technology is trained to detect a dent, a scratch, a broken part under specific lighting conditions. As a competitive feature, Jain (2020) declared that system could possibly notify if there is internal damage based on the external damages and prediction of possible collision happened. Further features with its accuracy is declared in the proceedings of the analysis. Added by Maggu (2018), pricing databases can determine the estimate for submitted claims with options of receiving check or scheduling a repair with an auto body shop.

6.2 Additional values

In comparison with traditional method, image recognition has revolutionalized the industry with three main impacts: Timely information, streamlined process, high processing capacity. The original impacts are specified in solid competitive values to the auto insurance claim process explained as follows.

Rapid and transparent assessment

Ageas UK Claims have presented that the Tractable technology has allowed their claim handlers to make real-time data driven decisions. With clear details of cars' conditions, the insurance employees could present to both customers and involved stakeholders regarding the conditions of the cars and their proposed repairment plans

according to Challand (2019). Furthermore, the regular assessment could be implemented in order to avoid deteroriating damages due to false operations.

Furthermore, there is a crucial assessment in auto insurance claims. That is first notice of loss or in abbreviation, FNOL. With the help of recognition, the vehicles are decided wether repairable or total loss at the very first notice. Kheytets (2019) has elaborated the traditional process as relatively subjective and time-consuming. The owners of the vehicle after damages reach the insurance representative and are asked with a set of pre-made questions regarding specifically the airbag blown, fluid leaking, etc. The assigned number is generated from the questions. The process is estimated to capture only 30% of total loss cases. The remaining vehicles are sent to the shop undergoing a teardown and the decision of total loss comes within one or two week. This is explained by the weak reliability of pre-made questions and non-experienced representatives to respond to the high volume of claims. However, Tractable technology has built a model that identify 90% correctly of total loss at the very first notice of loss by scanning the parts of the car and their locations as in the figure 18. The drastical change has saved the resources from representative, appraisers and also repair shops and eventually the insurance carriers.

| | Front Right Wing |
|--|-------------------|
| | Right Front Door |
| | Right Wing Mirror |
| | Grille |
| | Right Rear Light |
| | Boot Lid |
| | Rear Right Wing |
| | Right Rear Door |
| | Rear Bumper |
| | Rear Left Wing |
| | |

Figure 18 Scanning for car's exterior components (Cohen 2019)

For the repairable cars, the AI technology can detect damage severity, damage location, and estimated costs. From there, customers can expect the most excruciating questions regarding to repair plan, costs and reparing time by using Tractable Technology. For further visualization of how the estimating process works, figure 19 from Tractable depicts a overall display of back-end informations generated from the picture, including the damaged parts and their approximate cost calculation with transparency in less than three minutes. (Kheytets 2019a.)

| a less | | TRACTABLE AI Photo Based Assessment | | | | | | | |
|----------------|-------------------------------|-------------------------------------|-----------|-------------------------|---------------------------------------|----------------|---------|----------|--|
| | 0 | Vauxhall Corsa 2014 | | | | | | | |
| | BID VIN Reg | | | of Accident une 2019 | Point of Impact Front Centre | | | | |
| | Image Image £4330.90 50,490 | | | omer Claim ID | View online www.tractable.ai/oUidP | | | | |
| | | Repair Details | | | | Repair Totals | | | |
| and the second | | | | | topor totalo | | | | |
| | and a second | Part | Operation | Hours | Cost | | | | |
| | Front Bumper | Replace | 2.3 | £719.41 | Strip/Refit Labour | 8.6 | £288.62 | | |
| | | Part (OEM) | | | £287.00 | Panel Labour | 0.0 | 00.003 | |
| | | Strip/Refit | | 1.0 | £33.56 | | | | |
| | | Paint Labour | | 1.3 | £43.63 | Paint Labour | 10.1 | £338.96 | |
| | | Auxiliary Elements | | | £355.22 | Parts | | £1485.06 | |
| | | Bonnet | Replace | 3.0 | £380.68 | | | | |
| - | | Part (OEM) | | | £280.00 | Paint Material | | £890.70 | |
| 1 - Company | and Realling | Strip/Refit | | 1.2 | £40.27 | Total Ex VAT | | £3003.33 | |
| | | Paint Labour | | 1.8 | £60.41 | 20% VAT | | £600.67 | |
| 00 | | Front Right Wing | # Blend | 1.0 | £44.51 | Total inc VAT | 6 | 3604.00 | |
| | A STREET BOOM | Strip/Refit | | 0.5 | £16.78 | | | | |
| | | Paint Labour | | 0.5 | £16.78 | | | | |
| as an Reader | | Auxiliary Elements | | | £10.95 | | | | |

Figure 19 Car damage and cost estimation (Cohen 2019)

For the concept of Ravin AI, the advantages of acquiring CCTV photos allow Ravin AI to deliver the on-going record of the cars' conditions. Extracting features from processed images, Ravin AI could inform the owners in advance and propose solutions that can help to save the cost for more severe damages in the future. Besides, the right of customers' privacy is highly respected within the company. Therefore, the terms and conditions of data use need to be consented by the owners before the procedures. (Ekstein 2020.)

Increased reliability and scalability

During the assessment, there could be different views between policy holders and the insurance company. Al could be trusted as the objective way to ensure the rationales

in estimation over human sense. Therefore, the evaluation is based on the metrics from the images like the length of lines, the depth of scratches, the locations, etc. According to Kheytets (2019a), the process of reviewing results provided by the system is continuous and updating in order to ensure the increasing accuracy and consistency. Computer vision, as a part of AI, own the advantage of speedy processing time with little physical inspection. Being put in competition with the system, professional inspectors could spot with the same or more damages from the vehicles but it takes around thirty minutes. (Ekstein 2020.)

The reliability, on another hand, is reinforced by various methods of fraud detection, which is a striking issue, especially in the system of enormous data processing. The insurance carriers spend much effort identify the mistakes or intentional deceits such as whether the damages are on the same insured car or whether the same damages are reported several times with adjustments. Fraud detection happens at multiple levels, such as the location thanks to GPS coordinates, or features, such as background, lightning, colors (Jain 2020). With the customer's concern in mind, Ravin AI has proposed a short mobile phone "Walk around" solution which requires the insured to video record the vehicle in 360 degree view without intervention, enclosed with its time and location (Ekstein 2020). In the case of AI fails to process the photos, the system can ensure the cases separated to provide the confidence rate. The cases with low confidence rate are separated to be handled by professional appraisers. (Jain 2020.)

As also mentioned earlier in theoretical framework, the AI system works closely with a group of technicians and insurance experts, which reduces considerably the traditional way of numerous representatives, especially limited profesionally trained appraisers. With streamlined process and highly dependency on the machine, the technology companies claimed that little to none human intervention is required for assessment on the regular basis. Therefore, the system could handle a large scale of claims in minutes while ensuring the quality of final results.

Enhanced operational flow and customer experience

The above outperformance has enhanced drastically the efficiency of resources without compromising the stakeholders' interest' deliveries. According to Cohen (2019), by making the right decision at the right time, their customer could generate up to five hundred pounds of saving per claim. Within the auto insurance industry, while the pressure margins are high, this technology is crucial as the competitive edge to the business.

With rapid and transparent information, the cost of examination and transfering vehicle is reduced. The workflow is improved that the customer can happily expect their claim to be processed and possibly repaired in much shorter time. The repairshop and insurance companies are well prepared with their solutions smoothly with valuable real-time condition reports and less human-made mistakes while handling claims. Specifically, for body shops, the technicians receive enough information through the app to diagnose the vehicle's issues, ordering replacement parts, starting on the necessary tasks to complete the repair even before the vehicle's arrival (Maggu 2020). The figures show AI deployment could result in over three percent saving of total repair cost over the automobile physical damage book. (Kheytets 2019b.)

From the insurance firm's perspective, increased reliability and scalability eliminates the expenses and insufficiency of appraisers, representatives when dealing with a large amount of claims. The customers are served with objective report, having high reliability on the expert's assessment on damages, which is installed right in their phone (Cohen 2019). Tractable indicators also present up to 80% of claims processed touchlessly and 30% reduction in cycle time thanks to AI deployment (Kheytets 2019b). Besides, Claim Genius stated that the technology could cut up to 50% the processing time. (Jain 2020.)

The integration of technology does not eliminate completely the human involvement. Depending on the country regulations and their policies on carrier's, the human force is required. For the complexity of problems, experts are necessary for smooth processing such as internal damage or technical analysis. However, human intervention is expected to involve in around 20% to 30% in the total claims. (Jain 2020.)

6.3 Key to success and future outlook

The key to success is an abstract term regarding to several factors required from the clients. As image recognition is provided as services from the third party, this is a business to business model. Therefore, the technology is dealing directly with the carriers in term of building the system that works best for them. The insurance clients are usually the the judges to how well the image recognition services are performing from each of the participants. Usually the measurements are in comparison with the traditional processing method with high involvement of human and competitive analysis is created. (Jain 2020.)

There are criteria for accuracy could be first notice of loss, detection of damaged parts, severity estimation of damages, processing time, fraud detection and handling, learning curve of the system, etc. Additional maintainence criteria are management cost, expertise personnel requirement, alignment with company's infrastructure, model adjustment flexibility, support from service providers, etc.

From the service providers' perspective, to ensure the establishment and development of the system, criteria for success highly rely on the technical expertise, amount of data available for training. Technical expertise usually requires several data engineers holding Ph.Ds, who lead the team to build and manage the system. Besides, millions of photos are required in order to train the model to detect the damages with more precision.

Regarding to the future outlook, mostly companies are expecting a high adoption of insurance companies regarding the technology. Kheytets (2019a) believed that early adopters among the insurance organizations are expanding their competitive advantages. Another viewpoint declares the mission is to provide accessibility to everyone to their car's conditions with high level of accuracy, that enables online transactions by only the technology-generating details. (Ekstein 2020.)

As the nature of the revolution, technical aspects are critical to future outlook. Currently, the above criteria are acceptable and applicable within car insurance and other vehicle-related industries. However, the service providers are still competing on various solutions towards customized challenges proposed by the insurance carriers. Simultaneously, exceling in figures of accuracy, faster processing time together with less human intervention are believed to be the lucrative race.

7 Conclusion

This chapter highlight the outcome of the research answering directly the research questions stated from the beginning with comments from the author. The findings are briefly presented following the flow of questions stated earlier. Research limitations and recommendations for further researches are mentioned at the last section.

7.1 Research findings

Through the research from several companies which provides the services, there are several findings that are valuable to encapsulate the whole research. The recap is written by the author as a business student viewpoint towards the technology within the discipline of auto damage claim.

Brief concept of image recognition

In short, image recognition is the technology that extracts the solid information from the photos. The system is created by two elements: models and data. The models are created by engineers as the frame to guide the system at the very initial stage. In car insurance, the data as photos of damaged cars are fed into the system for useful feature extraction and simutaneously, as training material. With the input of more photos, the more the machine learns and increase its accuracy.

Efficient resourcing and satisfied stakeholders

The image recognition deployment has revolutionized the resourcing plan with three main impacts: timely and accurate information, streamlined process, high processing capacity. With transition from human-based to technology-based business, the processing cycle is smoothened and shortened. There are less mistakes created and increasingly high processing capacity. The policy holders are in control of their vehicles' conditions, expected shorter processing time and procedures. All the values are integrated to improve customer experience, customer retention and eventually the carrier's competitiveness in the market.

Key to success and possible outlooks

Briefly, the success of computer vision system depends highly on the expertise of technical engineers and the quality and amount of data acquired. As the result, the success of business practices in insurance carriers requires a set of technical criteria, which are various in each carrier company. Currently, the figures are already applicable in the business concept with 30% (Kheytets 2019b) to 50% reduced processing time (Jain 2020), up to 90% accuracy in FNOL (Kheytets 2019a), remaining only around 20% to 30% human intervention (Jain 2020), added value of outperformance in fraud detection.

Possible outlooks could be illustrated with more insurance carriers integrating the technology. The service providers are refining their models to achieve higher performance in the above figures with shorter processing time, higher accuracy in detection and estimation, thus less human intervention, and finally fraud detection.

7.2 Reflection on validity and reality

In the research, validity is guaranteed by the connection between the big questions, sub-questions and the design of questionnaire accordingly. The analysis also answer to each of the sub questions stated earlier.

Regarding to reliability, there is a limit of service providers due to the introductory stage of services and the nature of business to business companies. Four companies studied are the the well known in the image recognition applied in auto insurance. More over, the data is collected from high quality and certified sources such as interviews, speeches and own company's online sources. Therefore, the reliability is ensured.

7.3 Limitations and recommendation for further research

The main motivation of this research is to examine the hype of image recognition with in a specific practice, auto claim process from the business perspective. Therefore, there is limitations in the aspects covered in the study. There can be mentioned as: - Vehicle inspection requires transportation of the vehicle to the inspection stations such as company cases UVEyes, ProovStation.

- A few advanced steps in model training to enhance the accuracy including: data normalization, regularization and caliberation.

Within the related industry that the similar services can be ultilized, there are several research that can be conducted:

- Image recognition in the transformation of the industries (such as car dealership, vehicle transportation, and others requiring car inspection services).

- Establishment of competitive analysis between image recognition and human force in auto insurance industry.

- Deployment plan of image recognition for insurance carriers.

- Extracting information from image recognition information for insurance underwriting process.

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Appendices

Appendix 1 Interview invitation letter

Dear Sir/Madame,

My name is Bao Nguyen, a student from LAB University of Applied Sciences, currently pursuing bachelor degree in International Business. I am now working on the thesis regarding "Image recognition in auto claim process".

I believe that the experience in the field would make you ideal for valuable information to the research enquiries. Therefore, I hope to conduct a short interview with you regarding the services you are offering. Your shared knowledge and experience would be valuable to this study. And thus, create a great public understanding of this evolution in the field.

The purpose of the interview is to explore the image recognition mechanism and the values it brings to the auto claim process. The interview is set informal, including 6 main questions within around 30 minutes. The process can be conducted through online video platforms (Skype, Zoom, etc). If you are not able to participate in a personal interview, written answers would be much appreciated.

Please find the attachment of the questionaire together with this email.

In the case, that you are willing to participate, please suggest a time that we could proceed and I will try my best to be available. Please reach me if you have any inquiry. I am looking forward to your response.

Thank you and best regards, Bao Nguyen. Appendix 2 List of interview questions



Bao Nguyen b-nguyen@student.lab.fi Falcuty of Business Administration International Business

Interview questionaire

Research question: How image recognition is transforming the auto insurance claim process?

Image recognition and its mechanism for auto damage claim

How you define the concept of image recognition and its difference from the traditional vehicle damage claim?

How briefly the image recognition model is built? What are the types of data and how they are processed?

Added values to auto damage claim process

What values image recognition has added to the damage claim process?

What are KPIs used to measure the performance of image recognition? And how good they outperform the traditional method?

Key to success, challenges and future outlook in auto damage claim

What are key to success between services provider of image recognition in auto damage claim.

What is the future outlook of image recognition in damage claim process in auto damage claim.