Intelligent Car Crash Reporting System

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***Abstract*— Malaysia is one of the most traffic accident vulnerable countries in the world. This is due to the reason of high reliance on vehicles and roads as the major transportation in the Malaysian context. The gradual increase in road accidents has caused the congestion of Malaysian Emergency Response Services (MERS) which has further led to problems related to the failure of timely handling bulk of cases thus inadvertently causing fatalities. To mitigate the issues related to the inefficient emergency response measures, an intelligent car crash reporting system known as Autoport has been proposed. The aim is to streamline the process of car crash reporting, diverge the call traffic from the MERS hotline, as well as, reduce the prank calls by implementing machine learning and object detection for automating the reporting task. Once a user uploads a video for reporting, the proposed solution will detect the severity of the car crash and send rescue notification to required authorities via push notifications. The proposed solution is developed with the adoption of the Rapid Application Development methodology. The paper also highlights the system requirements gathering processes by the means of interviews and questionnaires. Besides, the accident severity detection model development and evaluation played a pivotal role in enhancing the validity of the work. This research also includes the analysis of User Acceptance Testing, further validates the proof of concept and viability of the proposed solution in streamlining and fastening the car crash reporting process for better rescue experiences.**

***Index Terms*—traffic accident, car crash reporting, car crash severity detection**

1. Introduction

Malaysian vehicle ownership has been ranked at the top in the world. Malaysian Automotive Association (MAA) stated that there is an average of 585,828 newly registered passenger and commercial vehicles yearly ranging from 2010 to September of 2021 [1]. While Statistics showed by CEIC data further proven that the total number of registered vehicles in Malaysia has reached a historical highest of 17,485,589 units dated in December 2020 [2]. Huge numbers of vehicles on the road have contributed to the high traffic accident rate in Malaysia. Statistic presented by reference [3] says that road accidents have increased from 414,421 cases in 2010 to 567,516 cases in 2019. Increasing the number of cases by about 37%.

The increment of road accidents does help in congesting Malaysian Emergency Response Services (MERS). There is an average of 36,500 calls handled by the 999 hotline per day from 2018 to February 2019 [4]. MERS also faced problems such as receiving non-emergency and prank calls [5]. There are about 5.8% of calls are categorized as non-emergency calls and prank calls such as calling due to punctured tires [4]. These issues have created a highly congested situation for emergency calls in Malaysia, leading to failure in timely handling the bulk of reported cases received.

The issues are worsened with the complex process of emergency reporting in Malaysia. According to former Selangor police chief Comm Datuk Noor Azam Jamaludin, MERS is adopting centralized management where calls are redirected to Putrajaya emergency operation centres [5]. The operator will attempt to understand the situation and transfer the call to the nearest authorities' station in handling the cases [5]. This led to long time required for authorities to be informed and depart for the rescue mission. Hence, all these issues must be taken into consideration to provide a more efficient way for car crash reporting, allowing the rescue mission to be done on time.

2. Domain Research

2.1. Concept of Car Crash Detection

The concept of car crash detection is the ability to detect an occurrence of a car crash on the road. There are several techniques proposed by other researchers in achieving the task. The detection is done either through car crash images, roadside surveillance video footage or through accelerometers of mobile phones or other IoT devices in detecting the impact anomalies. To achieve car crash detection through computer vision methods such as via camera or traffic surveillance video footage, training of Convolutional Neural Network (CNN) with car crash images will be required.

Reference [13] introduces an automatic car crash detection method based on Cooperative Vehicle Infrastructure System (CVIS). The system is built with YOLO architecture which can intelligently inform the vehicle moving in the same direction as the car crash scene to prevent the occurrence of secondary accident. The feature is done via the adoption of dedicated short-range communications (DSRC). In the meantime, notify the authorities to handle the scene via the 5G network.

Reference [12] proposed car crash detection using Arduino Uno and sensors in detecting the impact of a collision. If any impact is detected by the accelerometer of the car crash detection device, the device will send the accident signal along with the crash scene location to the nearest emergency station via GMS messages. A similar implementation concept can be seen in the work of reference [9] and reference [16].

2.2. Concept of Car Crash Severity Classification

Car Crash Severity classification is a concept of classifying and predicting the severity and injuries of a car crash. Reference [14] introduces the prediction of car crash severity in Malaysia by using Random Forest Model, in which the model is predicting the crash severity through variables such as weather, date, time, driver type, vehicle types and so on.

Reference [7] also uses a historical car crash dataset. The authors' focus is put on the United Kingdom. Their Deep Forest model can produce over 90% of accuracy with only 8 affecting features.

From studies of both reference [14] and reference [7], decision tree-based algorithm families such as Deep Forest, Random Forest, XGBoost and others can perform better in highly complex data as compared to neural network model families when training with less correlation input variables dataset, especially when the available dataset is small.

2.3. Factors Influencing Severity and Injuries of a car crash

Reference [7] has done their research in finding the top 17 influential factors affecting the car crash severity in the United Kingdom (UK) via Random Forest algorithm. On the other hand, reference [14] performs their research by ranking the influential factors of car crash severity via the application of Recursive Feature Elimination (RFE) in the Malaysian Historical Car Crash dataset. Combining both studies, similarities in influencing factors of severity can be found even though the research is done on two different geographical locations' datasets. Both studies reflect that weather, vehicle type, month, speed limit, vehicle movement and road surface conditions are highly influential in the car crash severity.

2.4. YOLOv5

You Only Look Once version 5 (YOLOv5) was created by Glenn Jocher in 2020 and has an official GitHub repository managed by Ultralytics [15] [18]. YOLOv5 is the enhanced version of YOLOv3, and it is a single-stage detector. Different from a two-stage detector such as the Faster Region-Based Convolutional Neural Network (Faster R-CNN), Fast R-CNN, Mask R-CNN and so on, it uses only a single CNN model to localize the bounding box of an object, as well as predict the class of the bounding box. In YOLOv5, the image is separated into grids and several anchors will be deployed to each grid to identify if the grid contains the target object [6]. For instance, if the image is separated by 9 grids and the number of anchors has been determined to be 3, 3 anchors will be deployed to each grid, resulting in a total of 27 anchors deployed on the whole image. An algorithm known as Non-Maximal Suppression will be used such that only the highest probability anchor is selected and be used as the bounding box of the target object [6].

Since YOLOv5 is an enhanced version of YOLOv3, it is also inheriting the characteristics of using k-means clustering to pre-set the number of anchors and the aspect ratio of the anchors. Then, the aspect ratio of the anchors will keep on updating throughout the training session and subsequently reach optimal results [10].

2.5. Faster R-CNN

Faster Region-Based Convolutional Neural Network (Faster R-CNN) is a modified Fast R-CNN which provides a faster detection speed without losing the accuracy. Faster R-CNN is proposed with the introduction of the Region Proposal Network (RPN) [11]. Faster R-CNN is a two-stage detector. It uses two CNN for the object detection task. The first CNN is used to localize and propose several candidate regions, while the second CNN is used to predict the class object for each candidate.

Whenever Faster R-CNN received an input image, it feeds the image to the first CNN which is known as RPN and uses a predefined sliding window to slide through every pixel within the image. For each pixel, a default of 9 anchors with different aspect ratios are deployed and used to suggest and localized the objects in the image [11]. The task of the RPN is used to learn and tune the optimal aspect ratio for the class object, as well as learning to have an accurate bounding box proposal for the target objects. These proposed bounding boxes will be cropped and subsequently feed into the second CNN for object class prediction [11]. By having such architecture, it allows the tuning of RPN and the actual object detection CNN individually, thus providing better accuracy as compared to other single-stage detectors, but with the cost of slower detection speed.

3. System Development Methodology

3.1. Rapid Application Development

The adopted system development methodology is Rapid Application Development (RAD). The first stage of RAD is started with requirements planning. In this stage, literature review, interviews, and questionnaires are all conducted to gather users' requirements [8]. The stage is followed by the user design stage. In this stage, the machine learning models and mobile application is developed iteratively and incrementally. The developed prototype will be shown to the sample target users for testing and gather their feedback for the next iteration improvements and undergo prototype refinements until the prototype is widely accepted by the sample testers. The finalized prototype will now be constructed into the real-world application which will be hosted in Amazon Web Services (AWS) in Construction Phase. Lastly, the constructed application will be undergone final system testing, regression testing and user acceptance testing and prepare for the cutover to replace the old MERS reporting mobile application.

3.2. Unit Testing

Unit test is conducted to test all the functional units of the proposed system. The test allows the identification of bugs and errors in the early stage and fixes them before running into the production deployment. In a unit test, the testing for backend data processing units, correct functioning in obtaining model detection results, and the API connections with the AWS services are all tested.

3.3. Integration Testing

Integration testing allows the assurance of good integration between each of the constructed units and between the units with the graphical user interface (GUI). The test will ensure the integrated modules can work as expected. To conduct the test, end-to-end testing is run for each use case such that both the GUI and the integration of the units can be tested. For instance, testing on making a successful login needs to ensure that the user will be redirected to the home page of the mobile application.

3.4. User Acceptance Testing

User acceptance testing (UAT) is a type of testing where the end-users are invited and tested on the functionalities of the mobile application to assess their acceptability towards the constructed system. In the test, users can assess if the finalized product is meeting the requirements that were raised during the data gathering phase through the questionnaire and interviews. It is the last testing that will be done before the system is pushed to the production environment and published to be used by the target end-users.

4. Research Methods

The research methods have been focused on questionnaires and interviews. The questionnaire has conducted to ask both open-ended questions and closed-ended questions to 50 target road users. While the interviews are conducted with 2 police officers and 1 MERS operator. The reason for selecting the questionnaire is due to its capability in reaching out to a large number of respondents in a short time. The respondents could be from various demographic and geographical locations, allowing better requirements generalizations due to the large samples. Moreover, the adoption of Google Forms can provide anonymity to the respondents, at the same time, easing the analysis of the responses via Google Charts. While an interview is selected where in-depth questions could be asked based on the respondents' answers. This results in a great in-depth understanding of the opinions and requirements of the respondents regarding the proposed system. The interview for the proposed system is conducted fully online via Microsoft Teams.

5. Results of Requirements Validation

Based on the results of requirements gathering, several problems are identified and validated. First, there is low satisfaction towards the existing system due to complicated and time-consuming processes in making the call for reporting. Secondly, participants are willing to stop by and send help if the accident reporting is in need. However, there are also reflections that they will only be willing to help with the prior conditions of not making the traffic to be congested. The MERS operator also reflects that there is an actual language barrier faced for the reporting with the existing system if the reporting person is a foreigner who is poor in English, Malay or Mandarin. Due to all these reasons, all the identified requirements are retained where the technical requirements for constructing the proposed system with performance, security and availability are listed in Table 1.

Table 1: Technical Requirements

Category	Choice	Remarks
Programming Language	1. Python 3 2. Kotlin	• Python 3.9 is used for machine learning model development and training • Kotlin is used for mobile application development
IDE	1. JupyterLab 2. Google Colab 3. Android Studio	• JupyterLab is used for machine learning model development • Google Colab is used for model training due to its strong GPU. • Android Studio is used for mobile application development
Database Management System	1. Amazon DynamoDB 2. Amazon S3	DynamoDB will be used to record textual data with Amazon S3 is used to store the uploaded video. Both databases will be used along with other AWS services for the best backend pipeline configuration for the proposed system.

6. Implementation

6.1. System Abstract Architecture

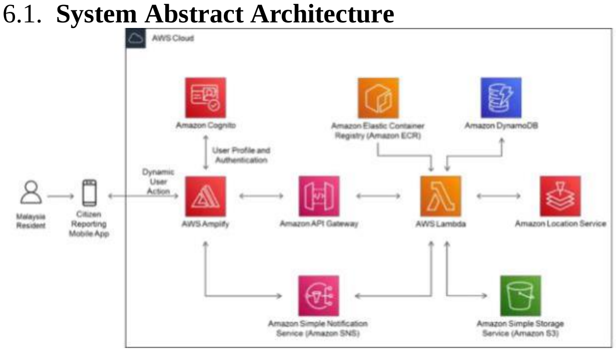

Figure 1: Abstract Architecture of Intelligent Car Crash Reporting System

Figure 1 is showing the abstract architecture of the proposed system. The AWS Amplify is used to connect the mobile clients with the backend services which are the AWS environment. Whenever a user is making an action, Amazon API Gateway helps to send the HTTP POST request to specific AWS Lambda such that the desired backend action can be done. For instance, processing and storing the uploaded video, making car crash severity detection and assigning authorities, calculating routes and so on. The Amazon Elastic Container Registry (ECR) is used to store a custom docker container image which is designed for both the car crash severity detection task and involved vehicle detection task. It is used to allow the hosting of large Python Libraries such as PyTorch in the AWS environment. Whenever a POST request is sent to the specific Lambda, the docker image of ECR is pulled and loaded to the lambda compute instance to perform the detection task and return the results to the mobile clients. The Amazon Location Services, Amazon DynamoDB, Amazon S3 and Amazon SNS is all connected to AWS Lambda, which are used to calculate routes, store the textual data, store video files and send push notifications to target mobile device respectively.

6.2. Car Crash Image Dataset

The car crash image dataset is collected from various sources. A large portion of the dataset is collected from the GitHub repository of traffic-net and the rest is from online sources of Facebook and Twitter, at the same time from some local car repair and towing centres. To experiment on the increment of precision, cat and dog images are added to act as the background images for the model training and results. The final dataset consists of 1,906 images.

The data labelling is done via the adoption of Roboflow and the images are labelled according to the car crash severity definition set by the United States National Highway Traffic Safety Administration (NHTSA) [17] [19]. This label also has been verified by Ts. Zarir Hafiz Zulkipli, who is the Head of Vulnerable Road User Safety and Mobility Unit (VRUM) at Malaysian Institute of Road Safety Research (MIROS), further proven the label validity.

Table 2: Class Label Description for Image Dataset

Class Label	Sample Image	Description
no_accident		Any vehicle that is in its original state as to how it should be from the factory.
minor		Any car crash where only little damage was found on the vehicles. For instance, scratches or slightly dented. The vehicle is still possessing the capability to drive away from the crash site. Having a low possibility for the driver or passengers to undergo any injuries.
moderate		Any vehicle that has significant damage but the damage is repairable. The crash has a strong possibility for non-fatal injuries to happen to the drivers or passengers. The vehicle has no more capability to drive away from the scene without towing.
severe		The vehicle has been undergoing strong damage including if the vehicle falls into the drain, strongly damage on the engine bay, having strong dented on vehicle doors, vehicle flip over or the vehicle is on fire. Drivers and passengers have a strong possibility to be dying from such kind of car crash.
fire		Any vehicle that caught on fire will fall under such category.

6.3. Malaysian Historical Car Crash Dataset

The dataset consists of 4,022 records of Malaysian historical car crash data in 2017. The dataset is obtained from the Malaysian Institute of Road Safety Research (MIROS). The obtained dataset is stored in excel format and consists of 4 different sheets, which the 4 sheets are identified as Accident Info 2017, Car Driver Info 2017, Injury Info 2017 and Ulasan 2017. Accident Info 2017 sheet consists of 70 columns and is used to record the basic information of the accident including the day, time, weather, road condition, location, accident severity and so on. Car Driver Info 2017 sheet consists of 30 columns and is used to record the involved vehicle's driver information. Injury Info 2017 sheet consists of 18 columns and is used to record the casualties in the accident. Lastly, Ulasan 2017 sheet consists of 6 columns. It is designed to record the accident testimonial done by the accident survivor. Report ID is used to connect all records across the sheet.

Data cleaning is performed to remove missing values, invalid latitude and longitude values and ambiguous vehicle damage descriptions in accident testimonials from the dataset. Data transformation is also performed to convert the latitude and longitude format from Degree minute second (DMS) to pure Degree format as both Google Location and Amazon Location Services are returning and receiving such inputs. After both data cleaning and transformation, the data is downloaded and performed vehicle damage severity labelling with manual methods and sent back to MIROS for validation.

The validated data consists of 1123 records of severe car damage, 1 record for moderate car damage and 1 record of minor car damage. From the validated dataset, it shows a strong correlation between vehicle damage severity with the car crash severity, which is measured by the casualties' injuries, giving a sign to abandon the model development for predicting car crashes based on variables such as the speed limit, weather, day, time and so on, and instead, directly coding the logic in the backend code.

6.4. Model Development

YOLOv5 and Faster R-CNN are both chosen as the target detection model for research. YOLOv5 is chosen due to its fast detection with good accuracy when a sufficient image dataset is given, while Faster R-CNN is selected due to its great accuracy for most of the scenarios. Due to the image dataset having a strong class imbalance, data augmentation has been done on the minority class. The data augmentation involved is including grey scaling, colour inversion, blurring and brightening of the minority classes' images. No image inversion is done as an upright vehicle and an inverted vehicle might have different vehicle damage severity. The results of training with augmented data are overfitted and it is believed due to the reason of repetitive viewing of similar images with different colours only. Thus, the data augmentation action is abandoned.

6.5. Model Evaluation

Table 3 is showing the top-performing models for car crash severity detection. Among all the models, although Model 2, 3 and 4 are all having better mean average precision (mAP), only Model 1 and Model 4 are considered the candidates for the proposed system due to their higher recall. High recall meant to be having more false positives but having fewer false negatives. If choosing a higher precision over recall, it might have the chances for a severe case to be detected as non-severe, causing a missing chance for the rescue of actual casualties. Among Model 1 and Model 4, unless there is GPU support in the backend, else Model 4 will never be taken into consideration due to its long processing time. In AWS, it is still possible to have GPU support for the detection task with additional setup of Amazon Elastic Container Service (Amazon ECR) and Amazon Elastic Compute Cloud (Amazon EC2). The setup would cost about 8173.08 USD for 3-year leasing. Due to limited development cost, the project is only followed with the selection of Model 1 as the proposed detection model.

For the involved vehicle detection model which is used to detect the involving vehicle in the car crash, YOLOv5s pre-trained weight that is trained with COCO Dataset is used. COCO Dataset is comprising objects from 80 classes which includes car, truck, train, people, motorcycle, bicycle and so on.

Table 3: Model Parameters and Model Accuracy

	Model 1	Model 2	Model 3	Model 4
Model Type	YOLOv5s	YOLOv5m	YOLOv5s	Faster R-CNN
Optimizer	Stochastic Gradient Descent (SGD)			
Learning Rate	0.01			0.005
Momentum	0.937			0.9
Weight Decay	0.0005			
Number of Epoch	155		250	41
Batch Size	32			7
Dataset	Finalized Dataset	Finalized Dataset	Finalized Dataset with Background Images	Finalized Dataset
Precision	0.579	0.668	0.755	0.627
Recall	0.602	0.584	0.563	0.767
Mean Average Precision	0.607	0.628	0.645	0.682
Detection Speed with GPU	28 seconds (22.5 FPS)	34 seconds (18.52 FPS)	28 seconds (22.5 FPS)	2 minutes 7 seconds (5 FPS)
Detection Speed with CPU	1 minutes 6 seconds (9.55 FPS)	1 minutes 15 seconds (8.4 FPS)	1 minutes 6 seconds (9.55 FPS)	41 minutes (0.26 FPS)

6.6. Detection Working Process

In the backend, the uploaded video is undergoing several pre-processing steps to read and resize the video to a correct aspect ratio. The pre-processed video frames are fed into a car crash severity model for severity detection. For any object that is being detected with severity (minor, moderate, severe or fire), the objects will be cropped according to the bounding box and subsequently feed the cropped images to the involved vehicle detection model for detecting the vehicles that were involved in the car crash.

7. Evidence of Outcome

7.1. Capture Video for Reporting

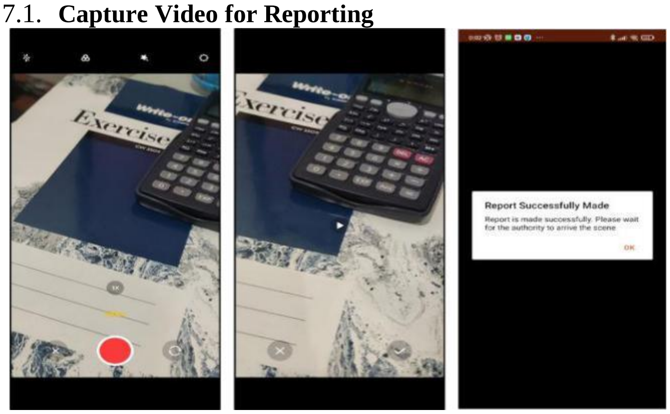

Figure 2: Capture Video for Reporting

When a user has logged in to their account on the proposed mobile application, the user could click on the Make Report bottom navigation bar and get access to capture the surrounding of the car crash scene. Upon completing the video capturing, the user could view, discard or make the reporting. Whenever the user is attempted to submit a report by clicking on the confirm icon button, the video is attempted to be uploaded to the backend. The upload action will be rejected if the video is identified as redundant reporting by the system. The user will receive a dialog box upon successful or failed reporting.

7.2. **Receive Detection Results**

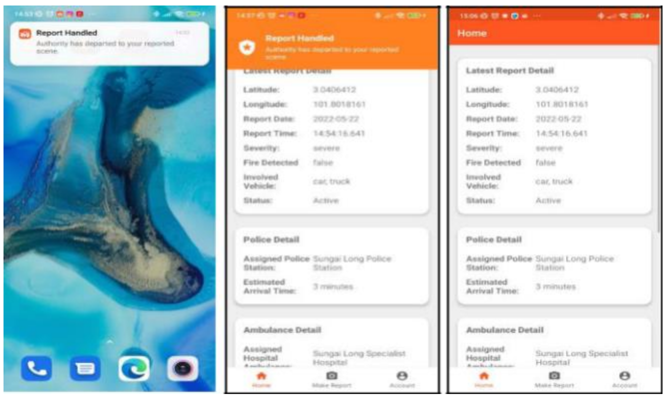

Figure 3: Receive Detection Results

The user will receive a push notification regarding the detection result when the model has completed the detection on the submitted video. When the user is within the mobile application, an in-app notification is given instead. When the user is clicking on the push notification, the user will be redirected to the home screen as shown in Figure 3.

7.3. **View Report History Detail**

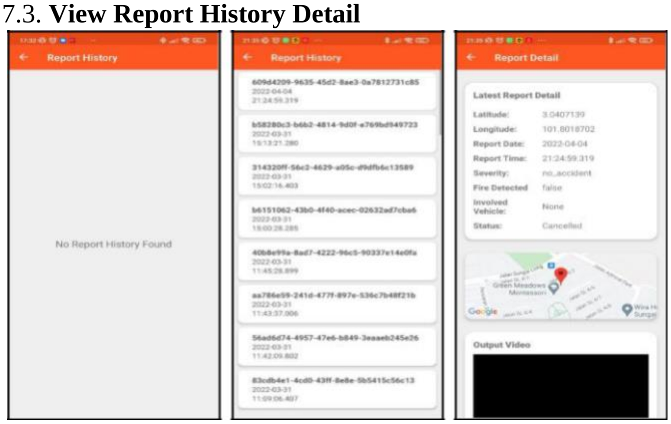

Figure 4: View Report History Detail

When a user has submitted at least a report with their account, they could access and view their past report history detail in the app. When the user clicked on any report history, they will gain access to view the report status, location, report date, time, crash severity, vehicles that were involved in the car crash, and gained the access to view the detection results.

8. Outcome of User Acceptance Testing

To validate the acceptance of target users towards the proposed system, 3 participants have been invited for the User Acceptance Testing (UAT). In the testing, all the functionalities of the proposed system are tested and assessed by the users through the answering of the questionnaire. From the UAT, all users are highly satisfied with the finalized mobile application. All the obtained feedback has been implemented resulting that the "Arrived" keyword in the ETA being in green when the authorities have arrived at the scene. All testers are highly satisfied with the proposed system except that they are in the hope of better accuracy in the detection results.

9. Future Enhancements

One of the crucial improvements that can be made for the proposed system is obtaining more image datasets to further trained the detection model. Secondly, further validates the conclusion of high correlations between accident severity and vehicle damage severity by obtaining more historical car crash datasets. This is because for the current project, the filtered data only consists of 1,125 records and it is too less for the conclusion to be generalized. All the images dataset and the historical dataset is suggested to be obtained from the Malaysian Police Department which the approach could reduce the wastage of historical data due to the ambiguous vehicle damage justification in the crash testimonial. Lastly, future enhancement of completing the authorities-end mobile application is also given, such that the full-fledge proposed system could be presented.

10. Conclusions

Through the studies, various problems have been met and successfully tackled. The conduct of a series of unit testing, integration testing and user acceptance testing also proved the viability of the proposed system in resolving the congestion of Malaysian Emergency Response hotlines. With the use of a machine learning model, it reduces the chance of missing out on the reported case as automation is shown in the proposed system, which also reduced the workload of MERS operators. Not only that, since the car crash reporting is required to be done through a registered account, it reduces the prank calls received by MERS. Even if any prank report is made, required legal action can easily be taken by tracking the user's account information. The proposed system also shows a better ability in tackling the language barrier when more language support is provided in the app with mature translation technology. If the proposed system is fully developed for both road users and authorities, it can foresee that the efficiency of car crash handling in Malaysia can significantly improve and ensured all casualties could be rescued on time.

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