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An artificial intelligence based crowdsensing solution for on-demand accident scene monitoring

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Abstract

Road traffic crashes have a devastating impact on societies by claiming more than 1.35 million lives each year and causing up to 50 million injuries. Improving the efficiency of emergency management systems constitutes a key measure to reduce road traffic deaths and injuries. In this work, we propose a comprehensive crowdsensing-based solution for the real-time collection and the analysis of accident scene intelligence as a means to improve the efficiency of the emergency response process and help reduce road fatalities. The solution leverages sensory, mobile, and web technologies for the real-time monitoring of accident scenes, and employs Artificial Intelligence for the automatic analysis of the accident scene data, to allow the automatic generation of accident intelligence reports. Police officers and rescue teams can use those reports for fast and accurate situational assessment and effective response to emergencies. The proposed system was fully implemented and its operation was successfully tested using a variety of scenarios. This work gives interesting insights into the possibility of leveraging crowdsensing and artificial intelligence for offering emergency situational awareness and improving the efficiency of emergency response operations.

Keywords: Crowdsensing; collaborative systems; artificial intelligence; accident scene monitoring; emergency management

1. Introduction

According to the World Health Organization, 1.35 million people die in road accidents every year; that is, one person is killed every 24 seconds [1]. Another 20 to 50 million are injured or disabled yearly on the roads [2]. Statistics show that road crashes are a leading cause of death worldwide, and the main cause of death among children and young people aged 5 to 29 [1]. Due to the devastating impact of roadside accidents, the heads of states

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attending the United Nations' 2015 general assembly adopted several sustainable development goals. One of those goals (SDG 3.6) consists of targeting a 50% reduction in road traffic deaths and injuries by 2020 [3]. Improving the efficiency of emergency management systems constitutes one of the measures needed to achieve that goal.

The discipline of emergency management focuses on avoiding risks and dealing with emergencies, particularly those that can cause deaths or injuries to the public [4]. The emergency management lifecycle consists of four main stages: 1) Prevention, 2) Preparedness; 3) Response; and 4) Recovery [4]. Prevention implies actions taken before the occurrence of emergencies (e.g., risk analysis and mitigation) to reduce their consequences. Preparedness consists of planning, training, and coordination activities needed to prepare for emergencies. Response constitutes the most critical phase of the process and includes the mobilization of the necessary emergency services and first responders. Recovery focuses on restoring the affected area to its original state by conducting activities such as repair and rebuilding.

Responding to road crash incidents in a timely and effective way is a challenging task. One of the main challenges facing emergency responders is the lack of situational awareness [5] about the incidents, such as The exact location of the incident, the number of impacted vehicles, the number of casualties, the scale of the accident, the injuries' severity level, the environmental conditions at the scene, and any other hazardous conditions that might be present and pose risk to the responders. Without this vital information and intelligence, it becomes difficult to accurately assess the situation and bring the appropriate help to the impacted citizens. For instance, underestimating the severity of injuries may lead to the lack of proper medical equipment and thus the delay in medical assistance potentially leading to fatalities. Indeed, the statistics show that up to 46 % of road traffic fatalities could be prevented if the right first aid assistance was available in those first moments [6]. Another situation could occur in which the person calling for help does not provide the exact location of the incident – a situation that is prominent in certain countries in which street addresses are not fully developed. Such a situation could lead to important delays in arriving at the scene. Another scenario in which hazardous material could be present on the accident scene (e.g., spillage of toxic substances or dangerous chemicals) could occur. Without knowledge of such information, emergency responders could be ill equipped to deal with the situation or even lack proper protective equipment to protect themselves.

With the rapid widespread of smartphones that come embedded with a variety of sensors (e.g., environmental sensors, location sensors, cameras and mics), users now hold in the palms of their hands' powerful devices that can be used as personal sensing platforms enabling the collection of a wealth of situational information. This integration of sensing technology in mobile devices opened the door for a new sensing approach and era – the crowdsensing era. The concept of crowdsensing implies the reliance on the crowd to perform sensing tasks and collect data about a phenomenon of interest (e.g., traffic conditions and accidents' occurrence) [7]. Using mobile crowdsensing for the collection of traffic and road related information could bring important benefits. The first benefit pertains to the easy on-demand deployment of a large-scale network of sensors since millions of mobile phones are carried everyday by the crowd. Most importantly, the ability to obtain information on demand about a particular accident before arriving on the scene could provide an important decision support tool for emergency responders, thus leading to fast, accurate situational assessment, and effective response to incidents and emergencies.

In this paper, we propose the use of crowdsensing and artificial intelligence for on-demand accident scene intelligence gathering as a means to improve the efficiency of the emergency response process and help reduce road fatalities. The proposed system consists of three main components: 1) citizens acting as participatory collectors of accident scenes' data; 2) emergency responders acting as consumers of the intelligence reports generated form the data collected by the crowd; and 3) a crowdsensing platform acting as intermediary between data consumers and data collectors by offering information management and data brokerage capabilities.

The rest of this paper is organized as follows: In section 2, a review of related contributions is presented. In section 3, we describe the architecture of the proposed mobile crowdsensing solution. In Section 4, we discuss how we used artificial intelligence for automatic accident scene analysis and accident intelligence report generation. The proof of concept prototype implementation is discussed in section 5, followed by the conclusions in section 6.

2. Literature review and research contribution

Some emergency related crowdsensing applications have been proposed in the literature. Kamijo et al. [8] proposed a tracking method to monitor and analyze traffic events at the roads' intersections. The solution proposed consists of an image-processing algorithm referred to as a spatio-temporal Markov random field (MRF) that can recognize certain traffic events such as bumping, passing, and jamming.

Wouters et al. [9] proposed the idea of using in-car data recorders as a means to monitor drivers' behavior and potentially reduce traffic accidents. The system proposed provides behavioral feedback by confronting drivers with their recorded driving actions. The conducted tests have shown an average estimated accident reduction of 20% and that the actual reduction rates vary depending on the transportation sector involved and the prior level of the fleet safety record.

Yousefpour et al. [10] proposed the use of an in-car device for the monitoring of various types of information, including the car speed, g-force, and location coordinates. This data is sent to a backend end server for analysis and detection of car crashes and potholes on the road.

Pan et al. [11] focused on the detection of traffic anomalies (e.g., accidents, protests, sports events, celebrations) using users' mobility patterns and social media data mining. In their proposed system, drivers' routing behaviour patterns on urban roads are analyzed and correlated with data extracted from social media about current events as a means to alert other drivers about anomalies on the road.

This contribution aims to offer an on-demand ability to gather accident scene data from citizens, and automatically generate accident scene intelligence reports, in a scalable, timely, and accurate manner. Unlike other approaches, the proposed architecture is tailored to the time sensitive and mission critical needs of emergency response operations. Furthermore, it leverages machine learning and artificial intelligence to offer a decision support tool for emergency responders, via timely access to automatically generated accident intelligence reports. To the best of our knowledge, this is the first contribution that leverages crowdsensing and artificial intelligence for real-time accident intelligence reporting.

3. The proposed solution

3.1. System design

Figure 1 depicts the system's high level architecture, which encompasses four main roles: 1) Accident affected citizens; 2) Citizens acting as data collectors; 3) Rescue teams and first responders acting as data consumers, and 4) An incident crowdsensing platform acting as an intermediary between collectors and consumers.

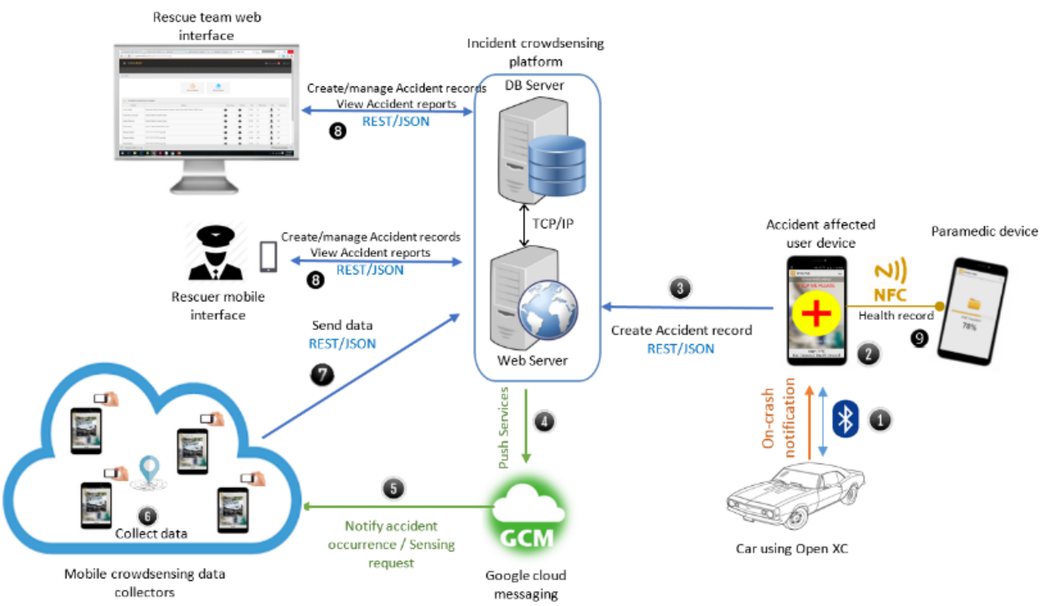


Fig.1. High level system architecture

3.2.1. The accident-affected users

In the envisioned system, drivers would be equipped with a accident assistance mobile app that would contain the driver's medical information (i.e., age, blood group, allergies, chronic diseases, current medication, major surgeries, and emergency contacts) and provide accident assistance services. Upon the occurrence of an accident, the car embedded collision sensor would send an on-crash notification to the mobile app over Bluetooth using the openXC car API. This notification would trigger the application to call for help, by sending a geo-tagged accident record creation request to the incident crowdsensing platform. Such a request will result in the broadcasting of an accident notification message to the registered drivers (data collectors) in the accident vicinity, who will collect image footage about the accident and send this information back to the crowdsensing platform. This last is responsible for verifying the obtained information and generating an aggregated accident report, which can be viewed by assigned police officers for better assessment of the situation and dispatching of the suitable rescue team(s) to the accident scene. Upon the arrival of the rescue team(s) on the accident scene, the accident assistance app can be used to easily transfer the accident-affected user's heath record to the paramedic's portable device, using near field communications (NFC). This information can be useful in administering personalized medical assistance to the affected user.

3.2.2. The data collectors

In the system, drivers are equipped with a crowdsensing mobile app, through which they receive a notification of an accident. This notification is sent by the incident crowdsensing platform to registered data collectors, using the Google Cloud Messaging Service (GCM). Upon receipt of an accident notification request, the crowdsensing app determines the data collector's proximity to the accident scene by comparing the accident location information (contained in the notification) to the device's current location. If the data collector is close to the accident scene (i.e., less than 100-meter distance), then the data collection screen is displayed to allow the user to take pictures of the scene, add a text description and an estimated severity level, which is then sent back to the crowdsensing platform for further processing. If the data collector is deemed too far from the accident scene, an alternate route is suggested to the user to avoid the accident scene related traffic.

3.2.3. The data consumers

Data consumers are those who are interested in crowdsensing data. In this case, data consumers are police officers and members of rescue teams who are interested in accessing accidents' records and reports, in better assessing the situation and provide more effective help to the affected citizens. Data consumers have access to accidents' related records using two types of interfaces: a mobile app and a web portal. Police officers have access to a crowdsensing consumer app allowing them to list accidents in an area of interest, view an accident report and footage, create a new accident record, and dispatch rescue team(s) to an accident scene. Rescue teams have access to a mobile app allowing them to receive accidents' notifications and accident details, in addition to collecting affected citizens' health records (using NFC) by tapping the citizen's mobile phone. Both police officers and rescue teams have access to a web interface allowing them to view all accident records, filter those records by area of interest, update an accident record (by adding observations and comments), and view a detailed accident report and related footage.

3.2.4. The crowdsensing platform

At the heart of the system lies a crowdsensing platform that receives accident notifications from accident-affected users' mobile applications and acts as intermediary between data consumers (e.g., rescue teams) and data collectors (i.e., drivers in the accident vicinity) for the collection of accidents' related data and the generation and dissemination of accidents' reports to authorized parties. To achieve that role, the crowdsensing platform encompasses a web server and a database server. It consists of different modules offering the following services: Authentication, Registration, REST-based communication, end-user service request, dispatching, data aggregation, data storage, as well as data analysis and reporting.

The authentication service relies on JSON Web Token (JWT) for representing messages securely between the crowdsensing platform and the client applications (i.e., the affected users, data collectors, and data consumers' applications), as well as the NodeJS passport framework for authentication purposes. The registration service handles the creation, editing, deletion, and suspension of users' accounts. The communication service offers REST interfaces enabling communication with affected users, data collectors, and data consumers. The end-user service request handles emergency requests from accident-affected users. The dispatching service initiates push notifications to the data collectors. The data aggregation service collects and validates the responses of the data collectors and provides data consumers a unified view of accidents' records. The data storage service stores the Binary JSON documents generated by the database onto disk. The data analysis and reporting service employs machine learning models to process and analyse the pictures collected from the accident scene, and automatically generate an accident intelligence report. This report contains relevant information needed by emergency responders for accurate situational assessment and effective response, such as *Total number of cars in the scene; number of damaged and undamaged cars in the scene; number of people in the scene; number of people lying on floor; number of people crouching; smoke or fire presence; weather condition at the scene; and road surface condition at the scene.* In the next section, we describe in detail how designed and developed the data analysis and reporting module.

4. Automatic Accident Scene Analysis using Artificial Intelligence

The concept of artificial intelligence focuses on enabling machines to mimic the cognitive functions of the human mind, such as interacting with the real world (e.g., speech and image recognition), reasoning and planning (e.g., problem solving), and learning and adaptation (e.g., self-learning). Due to its important application potential, artificial intelligence has been utilized in a range of contexts, including facial recognition, chat bots, search engines, robotics and many more.

Machine learning is a sub-field of artificial intelligence (AI) that provides systems the ability to learn and improve from experience without being explicitly programmed automatically. Machine learning focuses on the development of computer programs that can access data and use it to learn for themselves. Deep learning models are a class of machine learning that utilizes a multi-layered artificial neural network to continuous adapt its learning in an automated fashion. Such ability enables deep learning models to discover hidden patterns and process more complex data than regular machine learning models.

Due to the large number of car accidents that occur daily, manually analysing an accident scene to properly assess the situation can be a tedious and error prone task. In this work, we aim at automating the task for accident scene analysis using artificial intelligence – more specifically, deep learning models. In the coming sub-sections, we discuss the datasets we used to train the deep learning models, describe the process we used to train the models and tune their parameters. We end by presenting the automatic accident scene analysis results we obtained.

4.1. Datasets

To create a useful accident intelligence report, we focused on four types of information that would assist responders in situational assessment, namely: 1) Car damage detection; 2) Human pose detection; 3) Smoke and fire detection; 4) Weather and road surface condition detection. The car damage detection would help identify the number of impacted cars in the accident, and thus give an idea about the event's scale and impact level. Human pose detection would help identify some potentially problematic poses, such as lying on the floor or crouching, which are indicative of injuries and thus the risk and impact level. Smoke and fire detection is important to identify the risk involved for the people at the scene and get prepared to deal with such situations by bringing firefighting equipment and oxygen masks. Finally, the weather condition and road surface condition give an idea about the potential circumstances that caused the accident. To train the models to detect those four types of elements, the following datasets were employed:

- ***Car damage detection:*** The dataset for the car damage detection consisted of images of two types – damaged and undamaged cars. All images in the dataset have been taken from the Google images repository. The dataset consisted of a total of 1,408 images out of which 1132 were used as training images and 276 images were used to test the model.
- ***Human pose detection:*** The dataset for the human pose detection consisted of four different classes of images – standing, sitting, crouching and lying. These are the frequently seen poses of humans in already existing images of car accidents; thus, it has been included in the dataset. The images for this dataset have been taken from the MPII Human Pose Dataset [12] as well as Google images. This dataset consisted of a total of 926 images which was split into 727 training images and 199 test images.
- ***Smoke and fire detection:*** The dataset for the smoke and fire detection is composed of nearly 1000 images – 500 images of smoke and 500 of fire, out of which 200 were used for testing. All images have been taken from the DeepQuestAI fire and smoke dataset [13].
- ***Weather and road surface condition detection:*** The dataset for the weather images is composed of 1500 training and 400 testing images. Most of the images have been taken from the dataset for images for weather and road surface used in [14]. Additional images for the road surface and "windy" weather has been taken from Google images.

4.2 Deep learning model and parameters' tuning

Faster RCNN is one of the best models for object detection in still images and is from the TensorFlow Object detection API. Faster RCNN is a successor model to previous RCNN and Fast RCNN models. This model has three neural networks which namely feature network, region proposal network (RPN) and the detection network.

The function of the feature network is to generate all the good features from the given image and highlight these without any change to the size of the image. The Region Proposal Network generates the number of bounding boxes that has a higher probability of containing the object that the model is trained to detect. This network is made up of 3 fully connected convolutional layers. The final network is that of the detection network, which, as the name suggests, takes the input from the previous two networks (feature and RPN) and generates the final class of the object and the bounding box around it. This layer consists of 4 fully connected or dense layers, wherein the two common stacked layers (hidden layers) are shared by the classification and the bounding box regression layers.

For this research, we used pre-trained, Faster RCNN models. Thus no change will be made to the number of layers and nodes. However, all other parameters that have been fine-tuned for the detection. Table 1 summarizes the tuning parameters used for the different detection models.

Table 1. Detection models used and their parameters

	Car Damage Detection Model	**Human Pose Detection Model**	**Smoke and fire detection model**	**Weather and road condition detection model**
	faster_rcnn_resnet101_coco	*faster_rcnn_resnet101_coco (9211)*	*faster_rcnn_resnet101_coco (7362)*	*faster_rcnn_resnet101_coco (19157)*
first_stage_nms_iou_threshold	0.9	0.9	0.9	0.9
iou_threshold	0.4	0.4	0.5	0.4

Furthermore, to run all models on the same image and generate an accident intelligence report, we wrote a specialized script. The script created to run all models included the frozen graph of all the individual models – car detection, people detection, fire/smoke detection and weather/road surface detection. All the models were run in a sequential method in the order of cars, people, fire and smoke, as well as weather and road surface detection. After each detection, the NumPy array of the image is sent for the next detection and so on, producing the final image with all the associated detections. The final report generated after all the detections provides multiple details including the total number of damaged and undamaged cars, number of people sitting, standing, crouching and lying in the accident scene, whether fire and smoke has been detected in the scene and the type of weather and road surface that has been detected in the scene.

4.3 Classification results

Table 2 summarizes the classification accuracies of the models employed for the detection of the different elements, along with their confusion matrix. As shown in the table, the accuracy ranged from 92.38% for human pose detection, to 93% for weather and road condition detection. The accuracies for car damage detection and smoke/fire detection were 92.75% and 92.50%, respectively. Since human poses present multiple variations and subtle differences in certain cases, human pose detection posed the most challenge in this case. Nevertheless, with accuracies in the 90% range, and false positives/negatives ranging from 2 % to 5.5%, we can conclude that all models performed well for the task at hand.

Table 2. Deep learning models' performance

Model name	**Classification Accuracy**	**True Positive**	**True Negative**	**False Positive**	**False Negative**
Car Damage Detection	92.75%	47.46%	45.29%	4.35%	2.90%
Human Pose Detection	92.38%	22.24%	72.24%	2.76%	2.76%
Smoke and Fire Detection	92.50%	48.00%	44.50%	5.50%	2.00%
Weather and Road Condition Detection	93.00%	48.06%	45.10%	2.05%	4.78%

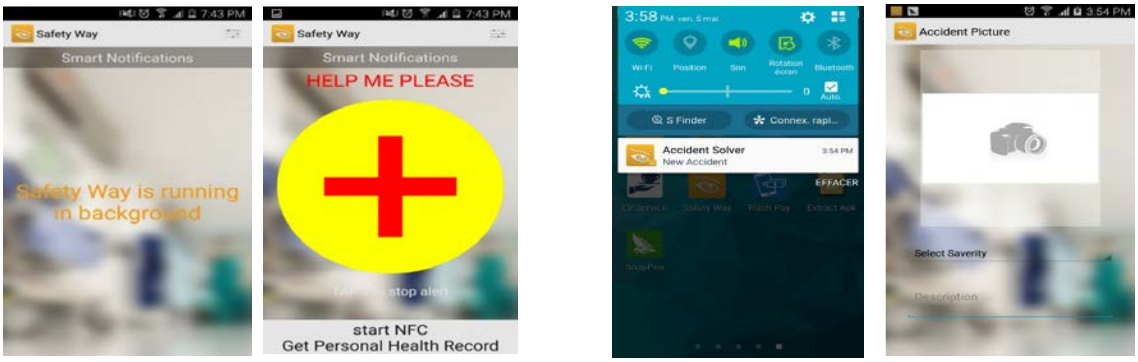
5. Proof of Concept Prototype

To build a proof-of-concept prototype of the system, we adopted the MVC (Model View Controller) architectural design pattern, as well as the MEAN stack. We implemented the functionalities of the web and database server and the web application using JavaScript, while the mobile apps were developed using Android studio V3.2.

MEAN consists of a software stack encompassing MongoDB, ExpressJS, AngularJS, and NodeJS, which is widely used for building dynamic web applications. MongoDB is an open source document database offering dynamic schemas for data persistence. It facilitates data storage of any data structure with JSON-like formats and can scale easily without any change to the application. In addition to MongoDB, we also used Mongoose, which is a NodeJS module and an object document mapper. ExpressJS was employed as a web development framework for NodeJS, while AngularJS 2 was employed as a front-end web application development framework enabling the implementation of dynamic user interfaces. NodeJS was used for implementing the REST APIs used for the communication between the server and the web and client applications, and for querying data from the MongoDB database. NodeJS is single threaded and asynchronous by design. Thus, it offers a non-blocking operation and returns an answer immediately after receiving a request, and generates a callback with the response later on.

As an authentication framework, we employed JSON Web Tokens (JWT) offering is a method for representing claims securely between server and clients as per RFC 7519. Also, Passport was employed as an authentication middleware for NodeJS that is integrated with express-based applications. Finally, to send new accident notifications and sensing requests to data collectors, we relied on Google Cloud Messaging (GCM) push notification service, while all other communications occurred using the implemented REST APIs.

Figure 2 depicts some screenshots from the implemented prototype. Figure 2-a shows the mobile application's main screen in which the application is continuously running in the background, monitoring the occurrence of accidents to call for help. Figure 2-b shows the help alert screen that is triggered upon the detection of an accident and is accompanied by an audible alarm sound. This occurs when the application receives a notification from the car's collision sensor (through Bluetooth). Upon pressing the help button, a help request containing the accident details (creator of request, location, and creation date/time) is sent by the mobile app to the incident management platform, the alarm sound is terminated, and the NFC module is activated in preparation for the sharing of the user's health record with the rescue team. Figure 2-c shows an accident notification received by a data collector, which, when clicked, opens the data collection screen through which the user can take a picture of the accident, write a text observation about it and indicate the incident's severity level. This information is then sent to the incident management platform that validates it and aggregates all responses to form an accident report.

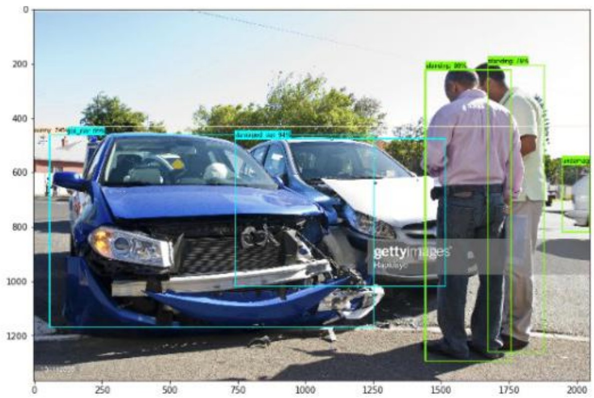


a) b) c) d)

Fig. 2. Sample screenshots – Mobile App

Figure 3 depicts examples of accident intelligence reports automatically generated by the analysis and reporting module when applied to some test images obtained from Getty images. In figure 3a, two damaged cars and one undamaged car were correctly identified, along with two people standing and the weather condition as sunny. The road condition however not detected in this case. In figure 3b, one damaged car and one undamaged car were detected – noting that the car on the left hand side was not identified due to the angle of the picture. Moreover, one person was identified as sitting, along with one person as crouching and one person as lying on the floor — finally, the weather condition as identified as sunny.

Total damaged cars: 2
Total undamaged cars: 1
Total people standing: 2
Total people sitting: 0
Total people crouching: 0
Total people lying: 0
Fire detected: No
Smoke detected: No
Type of weather: sunny
Type of road surface: Not detected



a)

Total damaged cars: 1
Total undamaged cars: 1
Total people standing: 0
Total people sitting: 1
Total people crouching: 1
Total people lying: 1
Fire detected: No
Smoke detected: No
Type of weather: sunny
Type of road surface: Not detected

b)

Fig. 3. Examples of accident reports generated

6. Conclusion

In this paper, we have presented a novel approach for intelligent, real-time accident monitoring. This approach combines the power of crowdsensing and artificial intelligence, to allow the collection of accident footage from citizens in the accident scene, and the automatic analysis of the footage to generate accident scenes' intelligence reports. The proposed solution aims at offering emergency situational awareness and improving the efficiency of emergency response operations.

In future work, we will enhance the analysis and reporting module to correlate the information extracted from multiple images about the accident scene, and generate one final consistent report. Furthermore, we will test the solution in a real-life setting, in collaboration with the road and transportation authorities.

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