Evidence-based Road Safety: an Automatic Road Traffic Crashes Data Management System (AutoRTC-DMS)

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1 Executive Summary

Road traffic crashes and associated road traffic injuries cause the death of approximately 1.35 million people per year. More than 90% of road traffic deaths occur in low- and middle-income countries. According to the world health organization, Africa has the highest road traffic injury death rates.

The Government of Rwanda has implemented different policies to reduce road traffic accidents including "Gerayo Amahoro" road safety campaign, road traffic cameras and speed limit controls, discouraging drink-driving, as well as improved road infrastructure. These policies are preventing many road fatalities but are not enough to end the losses caused by road crashes. In fact, only in 2019, the Rwandan National Police reported approximately 4,600 road accidents causing more than 220 deaths.

It is widely recognized that accurate reporting of road crashes and their causes can help in taking appropriate and effective road safety interventions. Unfortunately, road traffic crashes are under-reported, especially in low-income countries in which around 80% of road crash deaths are not recorded.

The AutoRTC-DMS (Evidence-based Road Safety: an Automatic Road Traffic Crashes Data Management System) project aims at designing and bringing to the market innovative tools and applications to record, analyze, and share road traffic crashes information in Rwanda. The system will support different roles involved in road traffic crashes handling: (i) road traffic police officers will be facilitated in road crashes management; (ii) emergency medical service operators will be automatically notified in the case of accidents. The notification will include all relevant details of the case like the severity of the accident, geolocalization, and other details to be agreed with the emergency medical service; (iii) road crashes data will support insurance companies in handling insurance claims as the accidents dynamics will be easily accessible; governmental and non-governmental institutions interested in road safety will be able to access and use road crashes archives and analytic in support of their decisions.

This document summarizes the finding of a broad analysis of the state of the art conducted to establish a common understanding of the road traffic crashes management field.

2 Context

Road Traffic Crashes (RTC) and associated Road Traffic Injuries (RTI) lead to the death of close to 1.3 million people and approximately 50 million injuries per year [1]. As per the World Health Organisation (WHO) definitions, Road Traffic Crashes are collisions which involve at least one vehicle on a public or private road that leads to the injuring or killing of at least one person [2]. Additionally, WHO defines Road traffic Injuries as “fatal or non-fatal injuries incurred as a result of a road traffic crash” [2]. Road traffic deaths account for more than 93% of all mortality in low- and middle-income nations (LMICs). According to the world health organisation (WHO) [3], Africa has the highest road traffic injury death rates despite a motorization rate of only 42 vehicles/1,000 population compared to a global average of 182 vehicles/1,000 individuals [3] with Rwanda’s motorization rate at 15 vehicles/1,000 individuals [4]. The Government of Rwanda (GoR) has taken significant efforts in ensuring road safety in the country. This has been done through initiatives such as the “Gerayo Amahoro” road safety campaign, installation of road traffic cameras in various parts of the country, enforcing speed limit measures on the road, discouraging drink-driving, and improving the infrastructure of the roads [5]. These measures have led to a significant drop in the number of road accidents, but they are not sufficient to bring it to an end. As of 2021, 1,024 road accidents were reported with 568 fatal accidents and 456 minor ones [6]. In most developing countries, reporting of road accidents is inefficiently done mainly because this task is often left to be done by traffic police and the people often involved in these crashes tend to avoid interacting with traffic police; preferring to negotiate with the driver. Another reason is the limited resources; thus, the police are most likely to prioritise crashes that involve more injuries, fatalities, or property damage [7–9].

3 Dimensions of Analysis

In this section, we define the set of criteria that we used to evaluate and analyse the different material that we used in this survey. These will be used in greater detail in other sections of the survey such as the related work and discussion sections. For simplicity there are mainly two major dimensions namely reporting tools/applications and contributing research work.

3.1 Reporting tools / applications

This dimension outlines the various real-world vehicle crash detection, reporting and analysis software in use. Five major categories have been identified. Softwares that have not been open-sourced are categorised as private whereas open-source softwares are categorised as public. The section on frameworks details major frameworks used in building the systems identified. Database technologies outline the various database management systems used. Finally, programming languages details the core programming languages used in the various projects.

3.2 Contributing Research Work

This dimension contains all the various research papers that were reviewed in relation to how Road Traffic Crashes are reported and managed in different parts of the world. We went ahead to further categorise this dimension into four major clusters.

1. **RTC Reporting.** In this cluster, we discuss all the various papers that talk about the various ways in which road accidents can be recorded as well as proposing and developing tools that can be used to report them.

2. **Predictive.** This cluster contains research papers that describe how to predict road traffic accidents. This cluster is further subdivided into two sub-clusters namely accident severity which contains research works that predict the severity of an accident and prediction models which contains papers that present different models that can be used in the prediction of road accidents.

3. **Preventive.** This cluster is made up of papers that propose various ways in which road accidents can be prevented. We further divided into three sub-clusters which include hot spots which discusses how to identify common places where road accidents occur and use them to warn other drivers, driver analysis which can be used to identify the drivers' state and use that information in determining whether or not they're likely to cause an accident and accident detection systems which contains papers that discuss the various systems that can be used in the detection of road accidents using different mechanisms as they will be discussed in the related works section.

4. **Road Safety Policies.** In this cluster, we have added papers that discuss the different policies that different researchers have deemed to be useful and effective in the fight to reduce road accident injuries and casualties. We further divided this cluster into three sub-clusters which include post care which includes some papers that discuss ways in which RTC victims can be better taken care of, road safety education which discusses various research papers that examine the effectiveness of road safety education in improving road safety and driver behaviour analysis which contains papers that mainly looked into analysing the behaviour of drivers for safe driving on the road.

4 Related work –> Overview of Road Crash Data Management Systems

Safety on the road is a particularly important aspect of road usage that everyone of us needs to observe as we go about our day-to-day activities. Researchers from around the world have done a tremendous job of studying about the various dimensions of road safety ranging from the different factors that lead to road accidents to policies that can be implemented to overcome them as well as using technologies to ensure that road safety is improved and that the losses that these accidents leave are curbed. This survey has reviewed the works done by researchers to identify the current state of the art tools and technologies that are used in the scientific world for road traffic crashes reporting and management. While carrying out the study we categorised the papers we reviewed into five major clusters: Reporting tools, RTC Reporting systems, Predictive, Preventive and Road Safety Policies.

4.1 Reporting tools

This section outlines various real-world vehicle crash detection, reporting and analysis software in use. Applications that have not been open-sourced are categorised as private whereas open-source software are categorised as public. Frameworks details core application frameworks used in building the systems identified. Database technologies outline the various database management systems used. Finally, programming languages details the core programming languages used in the various projects.

Overview of real-world reporting tools

Table 1 summarise the functionality of each real-world application identified. Two main criteria of interest are as to whether the source-code is available to the public and the second criterion specifies whether the application is available for use by the general public or only used by a select individuals, such as, law enforcement.

Table 1: Overview of Real-World Crash Detection, Reporting and Analysis Tools

Project	**Brief Description**	**Open Source**	**General Public**
Collision Reporting and Sharing System (CRaSH)	Collision Reporting and Sharing System is used by the Police in the UK to accurately report road crashes. The system runs on Azure Cloud and is available to users via a web browser. Users can upload photos and videos as part of the crash report. Uses Ordinance Survey Mapping to determine the accurate crash location [10].	No	No
iMAAP	iMAAP is an accident analysis software used in India. Developed by TLR in India, the system supports a multi-user, multi-department role-based access for Federal / National level deployments. It integrates easily with data sources such as driver licence, vehicle registration, road information, asset management and health injury databases [11].	No	No
Crash Report Sampling System (CRSS)	Crash Report Sampling System (CRSS) is used by the United States National Highway Traffic Safety Administration. It is used to estimate an overall picture of the crash site, identify highway safety problems and measure trends [12].	No	No
WHO GRSInfo	WHO GRSInfo is a mobile application that allows users to explore and interact with the data from the Global status report on road safety 2018 [13].	No	Yes
Vehicle Accident Hazard Notifier (VAHAN)	Vehicle Accident Hazard Notifier (VAHAN) is a web application that notifies nearby drivers in the event of a road accident. Additionally, it sends messages (SMS and WhatsApp) to the nearest police station and hospital with an accurate location of the accident [14].	Yes	Yes
Accident-Reporting-System	Accident-Reporting System is an Android application for reporting vehicle collisions. The general public can download the application onto their mobile devices and later on, use it to report incidents of vehicle crashes. These reports are sent to the necessary stakeholders (Police, Hospital, Family) [15].	Yes	Yes
Automatic Accident Detection and Monitoring	Automatic Accident Detection and Monitoring system automatically detects vehicle accidents and sends alerts to stakeholders. It utilizes real-time images through traffic cameras to provide instantaneous response to vehicle crashes [16].	Yes	No
ARGUS	ARGUS is an autonomous system that utilizes computer vision and machine learning techniques to detect road accidents and reports them in real time. The system ships with an interactive GUI dashboard for monitoring the accidents It uses a client-server architecture to achieve this [17].	Yes	No

Languages, Frameworks and Database Technologies

From the open-sourced applications, we explore what programming languages, frameworks and database technologies are used.

Table 2: Languages, Frameworks and Database Technologies

Project	Core Programming Language		Frameworks	Databases
	Back end	**Front end**		
Vehicle Accident Hazard Notifier (VAHAN)	Python	HTML, CSS and Javascript	TensorFlow Object Detection API	Does not use a Database Management System. Alerts are directly sent to relevant stakeholders.
Accident-Reporting-System	Python	Java	Pygeocoder – for geolocation processing Pillow – for image processing	MySQL
Automatic Accident Detection and Monitoring	Python	None	-	Azure Blob Storage, CosmosDB
ARGUS	Python	Python	YOLO neural network objection detection.	SQLite

4.2 Road Traffic Crashes Reporting

It is widely acknowledged that thorough reporting of traffic accidents and their causes can aid in the development of suitable and efficient road safety solutions. Unfortunately, traffic accidents are not adequately reported, particularly in low and middle-income countries where about 80% of fatalities are not reported. In this regard, Y. -K. Ki and D. -Y. Lee [18], points out that road intersections are where most fatal accidents occur. The authors then suggested a vision-based traffic accident detection algorithm as well as developing a system to automatically detect, record and also report traffic accidents at intersections. The proposed algorithm achieved a correct detection rate (CDR) of 50% and a detection rate (DR) of 60% as opposed to the earlier used sound-based accident system with a CDR of 1% and a DR of 66.1% which makes the proposed algorithm's performance quite remarkable. In the same manner, E. D'Andrea et al. [19] developed an artificially intelligent system to detect and report traffic-related events from twitter streams analysis in real-time. Using text analysis and pattern classification techniques plus a couple machine learning techniques, the authors were able to accurately predict and report traffic incidents that were tweeted about in a given area. The major downside of this system is the fact that not all traffic-related incidents are reported on twitter and at the right time of occurence, which makes the system less sufficient and not so applicable in remote areas especially those with poor/unstable network connections. In some countries, lack of an RTC reporting system has led to road accident victims having to entirely rely on the assistance offered by police officers whose untimely response to providing this assistance often results in victims suffering preventable injuries and deaths too as discussed by I. J. Mrema and M. A. Dida [20].

4.3 Predictive

With the rise in the usage of artificial intelligence and machine learning in various fields, researchers have investigated various ways in which these technologies can be used to predict road accidents as a way to improve road safety in different parts of the world.

Accident Severity

Alkheder et al. [21] analysed 5973 traffic accident records that occurred in Abu Dhabi over a 6-year period (from 2008 to 2013). The WEKA (Waikato Environment for Knowledge Analysis) data-mining software was used to build an Artificial Neural Network (ANN) model on the acquired data to categorise the degree of injury (accident severity) into four levels i.e. death, severe, moderate and minor accidents. The table below describes the four categories in detail.

Table 3: Accident categories

No	Accident Category	Description
1	Death	One or more persons die within 30 days of the accident
2	Severe	A person is injured and requires intensive care
3	Moderate	One or more persons are injured and detained in hospital for more than 12 hours
4	Minor	All persons involved are either not detained in hospital or detained for not more than 12 hours

The dataset was divided into both training and testing data. The prediction performance of the ANN model on the datasets was 81.6% and 74.6% respectively. The ordered probit model, which is considered a state-of-the-art mechanism for predicting accident severities, was used to evaluate the performance of the ANN model. The ANN outperformed the ordered probit model with an accuracy of 74.6% with the latter obtaining 59.5%. From the overall predictions made by the ANN model, 3% of the 5973 traffic accidents were fatal, 7% were severe, 31% were moderate and 59% were minor accidents.

Prediction Models

Shubham et al. [22] suggested different techniques for detecting and preventing road injury. These include Road crash tracking using smartphones, GSM and GPS technology, VANET, and other mobile devices. The discussed strategies use various sensors for accident detection, including accelerometers, pressure sensors, and machine learning algorithms, including neural networks, support vector machines, and classification algorithms. The researchers also identified the limitations of the proposed strategies and techniques which included recording of false positives in Automated Accident Detection systems using VANET for accident detection and that VANET may not perform well in different environmental conditions, such as rain. D. J. Lin et al [23] developed a high accident risk prediction model for analysing traffic accident data, and identifying high-risk intersections. The number of traffic accidents at intersections with similar environmental characteristics were used to predict the likelihood of traffic accidents in the future. Additionally, results from the study showed that environmental variables such as road width, speed limit and presence of roadside markings are significant predictors of accident incidence. From the paper, machine learning algorithms such Decision tree (C4.5), Bayes Net (BN), Naïve Bayes (NB), Multilayer perceptron (MLP), Deep Neural Networks (DNN), Deep Belief Network (DBN) and Convolutional Neural Network (CNN) were used to build the traffic intersection risk prediction models.

4.4 Preventive

Several researchers on the other hand have focused most of their work on the prevention side to come up with various ways in which road accident fatalities can be reduced by avoidance.

Hotspots

Hotspots are accident prone areas on a given road and thus identifying them can significantly affect the reduction of road accidents and the damages they cause. For this reason, researchers in the transport domain also tend to spend time in coming up with various ways in which these accident hotspots can be identified and used to improve road safety. A study by B. Ryder and F. Wortmann [24] revealed that through analysing real-time data collected from connected vehicles, hotspots could be detected and classified in order to improve driving behaviour by providing drivers with the knowledge that certain areas on the road network are more dangerous than others, and this information could be shared in real time. This means that new hotspots could be ubiquitously detected and drivers alerted right away which on the other hand could help in reducing the number of accidents occuring in those spots since drivers would then approach them with caution. In this study, video data captured by the smart phones mounted on the vehicle's dashboard was used during the identification of these hotspots. Some of the limitations in this study include a driver's interpretation on the correct smartphone setup and position in the vehicle, which can lead to scene obstruction or poor field of view if the phone is incorrectly positioned thus not getting correct video data, adverse weather conditions, such as heavy rain, and videos captured during the night, all of which can affect the quality of the video data being captured thus making it less accurate for the classification of the hotspot. Daphne Wang et al. [25] carried out a study to identify the hotspots in Kigali using the Road Traffic Crash (RTC) report data from the police and high frequency road users, from which hotspots were identified through kernel density estimation. From the study, 25 hotspots were identified, and all of these were less likely to have unpaved roads as well as the road narrowing and more likely to have pedestrian walkways, factors aiding pedestrian crossing and poor road surfaces. The study further revealed that those hotspots with fewer urban characteristics such as road safety features, motor vehicle density, and pedestrian safety features, have significantly decreased odds of being high mortality risk hotspots as compared to those with more urban characteristics.

Driver Analysis

Among the causes of road accidents, driver inattention is stated as one of them and this can be brought about by various reasons. One of them is fatigue which can lead to drowsiness. Chang et al. [26] proposed an active Drowsiness-fatigue-detection (DFD) system that automatically implements related road-safety procedures to improve road safety. The proposed system is composed of a pair of wearable smart glasses which based on eye closures detect the driver's drowsiness and fatigue, an in-vehicle infotainment telematics platform which upon detection of a DFD will transmit a (DFD) warning command to the in-vehicle speakers to alert the drowsy driver and rear lights of the vehicle to warned other drivers in front of him/her, and a cloud-based management platform.

Accident detection systems

S. Jamal et al. [27] developed a mobile application that can be used to detect a crash based on the speed variations, acoustic waves, and vibration waves of the vehicle, provide the drivers with real-time-information about the road conditions through push notification as well as alerting the driver if they exceed the speed limit of a given road and all these put together would help in preventing and reducing the possible number of road traffic crashes in regions where this application was appropriately used.

4.5 Road Safety Policies

Threats to road safety are caused by multiple contributing factors, several research have commonly highlighted the key factors that affect road safety, namely road infrastructure condition, weather, road user behaviour, accidents hotspot and traffic congestion.

Road infrastructure condition

A well maintained and conditioned road promises better driving and safety as compared to poorly conditioned roads which increase the probability of accidents. M. Eskandari Torbaghan et al [28] suggest that Regular road inspections and proactive infrastructure asset management are important to ensure road quality and safety, they found that artificial intelligence, particularly machine and deep learning and sensing and IoT are technologies employed to inform the condition of the road surfaces and validated by either field trials or case studies. These technologies have shown promising results for detecting road defects causing accidents.

Road safety education

There is an excess of young drivers involved in accidents and traffic fatalities. Pre-driver education initiatives to address this issue have not exactly been a success. Damian Poulter in [29] employed the framework of the theory of planned behaviour (TPB) to analyse the success of a UK-wide educational initiative that aims to modify pre-drivers' attitudes toward driving safety, and conducted 2 experiment that revealed tha following the educational intervention, there was a slight, short-term improvement in some pre-driver beliefs, but no change in other views. There was also some indication of unintended consequences.

Road user behaviour

The behaviour of the road users (i.e., both drivers and pedestrians) also play an important role in road safety. From a driving behaviour perspective, speed, fatigue, seat belt usage and driving under the influence of alcohol and drugs are found to increase not only the road accident rates but also the severity of a crash. To investigate the driving behaviour,

M. Eskandari Torbaghan et al. [28] reviewed thirteen selected studies where six of them used machine learning and image processing, four used sensors on mobile phones, three on remote sensors, and one article was attributed to IoT. More than half of the studies used field trials to validate their proposed approaches, while four of them failed to validate the developed models and technologies in the real world because they were only tested in a simulated environment.

4.6 Popular Tools and Technologies

This section examines the various machine learning or deep learning models used by the various projects examined.

Table 4: Popular Tools and Technologies

Project Name	**Description**	**DL/ML Model**
Crash Detection	The project makes use of a combination of CNN and LSTM as its main Deep Learning model. It takes an input frame or a sequence of frames and predicts the probability of an accident occurring, with a location the accident is likely to occur.	Convolutional Neural Network (CNN) Long Short-Term Memory (LSTM)
ARGUS	Vehicles are detected in real time using the YOLO deep learning model	You Only Look Once (YOLO) object detection model.
VAHAN	Vehicles are detected in real time using the Tensorflow deep learning model	Tensorflow Object Detection Model
Intelligent Traffic Accident Prediction Model for Internet of Vehicles With Deep Learning Approach	These models are based on the Crash Potential Index (CPI) to determine the risk level of vehicle lane changes	Fault tree analysis K-means clustering
Automatic traffic accident detection based on the internet of things and support vector machine	Employed SVM algorithm in detecting accidents	Support Vector Machine (SVM)

5 Discussion

5.1 Overview

From the reviewed real-world applications presented in the related works section, all open-sourced projects used the python programming language as the core programming language. One reason might be that there are numerous frameworks available in python for machine learning/Artificial Intelligence processing tasks. The database management systems of choice were mostly relational databases. From the contributing research work, it was discovered that there are quite a few reporting tools available especially in the Rwanda and Africa at large, thus revealing that there is still a need for such kinds of tools that can also be accessed by different people in order to report crashes instead of only relying on the traffic police officers to do all the work.

The above graphic shows estimated road traffic death rate (per 100,000 population) from WHO. It can be seen that road accidents have continued to claim people's lives from different regions even with all the various measures that different countries have put into place to keep these numbers in check. Furthermore, Africa still has the highest number of lives lost to road traffic accidents and the graphic below shows this in detail.

The above graphic is a summary of the road traffic death rate (per 100,000 population) categorised by gender from 47 African countries. It can be seen that Zimbabwe has the highest number of male lives lost (approximately 67) and Seychelles has the lowest (approximately 17). Liberia has the highest number of female lives (approximately 24) and Mauritius has the lowest (approximately 4). We can also conclude that in Africa, more male drivers lose their lives in road accidents as opposed to the female drivers. Rwanda on the other hand, loses approximately 43 male drivers and 16 females (per 100,000 population). This continues to happen even with existing countermeasures such as "Gerayo-Amahoro", speed cameras and others that the government of Rwanda has put in place. We believe that with a good tool to report these road accidents, one that will enable other road users to report accidents (instead of only traffic officers), better measures can be put in place and more informed decisions can be made using the data that the proposed system will capture.

Most decisions taken to improve road safety rely heavily on road crashes data, which makes the data a back bone of a country's road safety system. The data is obtained through various methods and clustered to form a road traffic accident database, these methods include but not limited to victim self recording of events, person in-charge from an institution and automated or non-automated intelligent systems. Errors in this data will lead to misidentification of dangerous accident leading spots, projection of false estimates pertinent to accidents and fatality rates, and detection of wrong parameters responsible for accident occurrence, thereby making the entire road safety exercise ineffective [25], It has been found that analysing police RTA (road traffic accident) reports alone could potentially misinform policymakers, planners, and accident prevention practitioners. These data should be analysed in conjunction with hospital admissions and suggest that information produced by hospital RTA injuries produced less biased data [26]. The first step of the development of an effective safety management system is to create reliable crash databases since the quality of decision making in road safety depends on the quality of the data on which decisions are based [27]. It however has to follow guidelines to effectively capture different data points necessary to RTA and also take into account different types of users of the data in order to achieve accurate and correct RTA reporting and help achieve better road safety.

5.2 Trends

Road Safety Actors

Generally, the definition and the application of a road safety action plan necessitates the integration of multiple road safety actors [28], which can also be referred to as road safety experts and have the power to make decision related to road safety and therefore important to be taken into consideration and help ensuring their decision are well informed.

Generally they include:

1. **Governmental institutions**: Transport & logistics ministry, infrastructure policy committees, etc
2. **Regulators**: Police, hospitals, industrial companies
3. **Associations**: schools, insurance companies, non-profit road safety companies
4. **Road users**: drivers, cyclists, pedestrians

Crash Data

Crash data need to be supplemented by other information, including road inventory and survey data of key behaviours, enforcement data, and emergency and medical system quality data [30]. Crash classification needs to take into account that crashes are multi-factor events and that all crashes have a chain of events leading to the collision and to subsequent damages and/or injuries. It propose a crash data collection form guides the users to report the crash narrative, to distinguish the different events leading to the collision and to collect them with a standard procedure, reporting for each traffic unit, the information is divided into six basic forms [30]:

1. Crash form includes:
   (a) Basic data
   (b) Emergencies
   (c) Location
   (d) Crash type
   (e) Crash scene
   (f) Sketch
2. Road and Environment form includes:
   (a) Road features
   (b) Pavement
   (c) Environment
   (d) Road signs
   (e) Work zone
3. Vehicle form includes:
   (a) Basic data
   (b) Owner
   (c) Insurance
   (d) Function: (commercial, public, private, etc)
   (e) Vehicle conditions

   (f) Chain of events (controlled manoeuvre prior to the beginning of the sequence of events, evasive manoeuvres, collision manner, events after the collision)

   (g) Damages

4. Driver form includes:

   (a) Identity

   (b) Driver licence

   (c) ID data

   (d) Conditions

   (e) Safety devices

   (f) Hospital data

5. Passenger form includes:

   (a) Identity

   (b) ID data

   (c) Conditions

   (d) Safety devices

   (e) Hospital data

6. Pedestrian form includes:

   (a) Identity

   (b) ID data

   (c) Chain of events

   (d) Conditions

   (e) Hospital data

Road Traffic Descriptive Features

Traffic accident data analysis is one of the promising approaches for improving road safety [28]. By taking into account multiple factors (e.g., infrastructure, weather, driver behaviour, etc.), it allows measuring the impact of traffic accidents on road security. Table 5 displays various descriptive features that machine and deep learning algorithms can rely on to build accident prediction models.

Table 5: Road descriptive features

Characteristics	**place**	**Vehicles**	**Victims**
Accident identifier	Roadway category	Vehicle identifier	Basic info: • names • age • gender • date of birth
Time: • day • month • year • hour • minute	Road identifier	Vehicle category: • Sedan • SUV • Truck • Bus • Sport	Victim place in vehicle
Location: • city, • town, • province, • address, • GPS	Surface condition	Number of occupants	Injury level: • Minor • Major • Severe
Weather condition: • Rainy • Sunny • Foggy • Cloudy • Stormy	Infrastructure type: • Road • Bridge • Tunnels	Manoeuvre before crash	Travelling reason
Intersection type if exists	Near school indication	Moving obstacle	Existence of security equipment
Collision type: • Head-on • Side impact • Single vehicle • Multi vehicle • Blind spot • Rollover	Roadway length	Fixed obstacle	Security equipment usage
	Roadway width	Initial shock point	Pedestrian action
	Traffic regime		Pedestrian location at time of crash

5.3 Limitations Of Existing Systems

1. Systems designed to support police officer **ONLY**, leaving behind other actors like road users, insurance company, medical emergencies personnel, etc
2. Use of self-reports as the primary source of information can be associated with biases such as social desirability
3. Limited information about RTCs outside of the police reports which on the other hand creates a single point of reference that comes with quite a number of limitations and challenges in terms of accessing information, heavy load on the police officers collecting the data thus making the information prone to errors.
4. Some of the existing applications only work on android devices which makes it hard to access them on devices running other operating systems thus leaving out potential users that could benefit from the developed applications.
5. The open-source projects reviewed followed the monolithic approach in their implementation strategies. A challenge with this is that as the application scales, maintaining it will be somewhat difficult. A more modern approach is to use micro services.

5.4 Recommendations

Crash reports were, are, and will continue to be useful for all road safety analyses as long as researchers recognize their limitations and use them with caution. Crash reports are likely to contain missing or inaccurate information mainly in crash location and time, severity, victims characteristics and other contributory factors. A more modern approach for developing this system is to go with microservices. Micro-services offer enormous advantages such as high reliability, easily maintainable code, faster deployment and troubleshooting. Most research works do not cater for post-care services after an accident, which is a very vital thing that cannot be left out. We recommend considering these kinds of services in order to ensure that the victims of the accidents are in better conditions and recovering from the injuries they sustained.

6 Conclusions

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