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Automated Accidents on Road Analysis: An Overview of State of the Insights

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Abstract

Nowadays, people's lives are becoming more and more luxurious with the use of technologies. Everyone wants ease and comfort. The trend of having personal vehicles for daily-based usage is increasing rapidly. As more and more people are buying vehicles, the traffic burden is increasing on the roads, causing accidents. When an accident happens, people get injured, and if the emergency services like medical aid are not given on time, then it may cause death. In the upcoming era, the idea of smart cities would be utilized, where every facility and service would be centralized and connected to a server; therefore, devices will be used to send a signal to the nearest emergency response center when an accident is detected on CCTV footage. This work reviews accident and accidental vehicle analysis through automated approaches. The areas of applications are highlighted along with the recent trends and practices discussed in this article.

Keywords: Accident detection, Road safety, Classification, Review, Smart cities

1. Introduction

As technology is going to be more advanced, this makes people's lives more luxurious, and with other facilities, the trend of buying private cars is also increasing gradually. This trend increases the traffic burden on roads which causes road accidents to increase day by day, creating serious security and safety problems (Zhao, H., Yu, H., Li, D., Mao, T., & Zhu, H, 2019). Motorway smashes the mounting distress of administrations and is climbing to become one of the primary avoidable grounds of the expiry of humans, specifically in emerging kingdoms (Engelbrecht, J., Booysen, M. J., van Rooyen, G. J., & Bruwer, F. J., 2015). Half of the expiry proportion of humans is because of the absenteeism of speedy healing facilities to injured people at the misfortune scene. One of the core motives for the extraordinary passing away proportion is the nonexistence of later-mishap healing attention. In that suggested architecture, researchers industrialized a testbed with an archetype that can determine misfortunes on a thoroughfare by expending keen instruments entrenched in automobiles, which can mechanically communicate tragedy amenities (Khaliq, K. A., Raza, S. M., Chughtai, O., Qayyum, A., & Pannek, J., 2018). Different approaches are used to reduce the death rate due to accidents on the road; like a smartphone application is developed, once a misfortune is noticed, it automatically notifies about the accident and its location through a cellular infrastructure to the nearest emergency response center, which will dispatch the team for medical services. Figure 1 shows the architecture of mishap uncovering using smartphones presented in one research work (Khalil, U., Javid, T., & Nasir, A., 2017, November).

Fig. 1. Use of smartphones for the detection of an accident and response (Khalil, U., Javid, T., & Nasir, A., 2017, November).

According to a survey, one person dies every minute due to traffic accidents worldwide (Li, J., Cheng, H., Guo, H., & Qiu, S., 2018). Figure 2 depicts the number of automobiles and mishaps occurring in China from 2012 to 2016, which shows a very alarming situation.

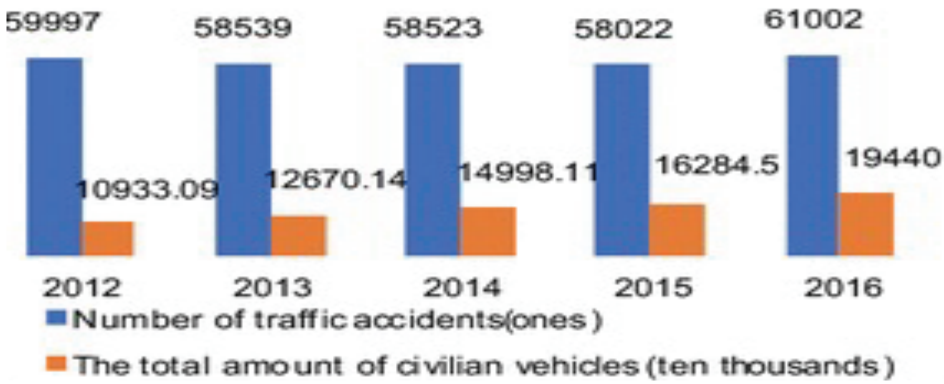

Fig. 2. Graphical representation of traffic and traffic accidents in China from 2012 to 2016.

Another survey says that 49% of the death ratio is because of roadside accidents (Ali, D., et al., 2020). This means 1.2 million people die every year due to traffic accidents (Mondal, P., 2011). A managing system for accidents can control traffic and emergency systems (Juliet, S. E., Sadasivam, V., & Florinabel, D. J., 2014). Precious human lives are gone wasted due to traffic accidents happening worldwide, which is a very alarming situation. To tackle this problem, such kind of system is needed in which there should be a sensor, closed-circuit television (CCTV) camera, or a smartphone that should have trained in such a way that it can analyze and detect an accident when it happens to a vehicle and quickly notify the relevant emergency response center about the location of the vehicle so that they may dispatch an ambulance for accident site so that effected people may get first aid on time and death ratio due to traffic accident may be decreased. There are different accident detection and classification techniques on which works have been done. The driver of the vehicle may be a primary cause of an accident on the road due to its careless attitude or avoidance of traffic rules which may cause many lives in danger; therefore, a profound erudition practice is utilized to examine and categorize the driver's behavior that whether his driving style is usual, violent, unfocussed, sleepy or drunk (Shahverdy, M., Fathy, M., Berangi, R., & Sabokrou, M., 2020). An intelligent transportation system (ITS) based method is used to detect traffic incidents by examining the lane altering the vehicle's speed (Sheikh, M. S., Liang, J., & Wang, W., 2020). Classification of vehicles is also done using a convolutional neural network (CNN) (Wang, S. Y., et al., 2020) integrated with the statistical moment's layer, also known as ICNN (Zhao, Y., Hao, K., He, H., Tang, X., & Wei, B., 2020), which extracts the statistical moment's features from the feature maps gained from convolutional layers (Tuama, A., Abdulrahman, H., & Magnier, B., 2020, January) as it is observed that the installation of CCTV cameras on roads and traffic signals is a common practice now. Data acquired from these cameras can be used for different purposes in which vehicle accident detection is also included. An integrated two-streamed convolutional network architecture is suggested, which accomplishes instantaneous detection, tracing, and close mishap recognition of highway consumers by using the transportation statistics obtained from CCTV cameras mounted on roads (Huang, X., He, P., Rangarajan, A., & Ranka, S., 2020).

2. Accidents Analysis for Smart Cities

Classification of accidental and non-accidental vehicle images can be used for different purposes in different areas for the benefit of mankind. To add more comforts and security to people's lives, the idea of smart cities is introduced (Ghosal, A., & Halder, S., 2018). Building intelligent systems for smart cities: issues, challenges and approaches. In (Ghosal, A., & Halder, S., 2018) Builders and construction companies focus on making intelligent city projects because the trend is going towards it. A smart city concept is a setup in which contacting groundwork, figuring capitals, distinguishing substructure, and statistics analytics organization form the mainstay of the cyber-physical system (CPS) (Lee, J., Azamfar, M., Singh, J., & Siahpour, S., 2020) and empower synchronized procedures of trade and industry, administrative, societal, traditional and inner-city happenings (Kummitha, R. K. R., & Crutzen, N., 2017). Figure 3 shows the infrastructure of the smart city concept in which all the daily life process is connected and supervised through a centralized system. In smart cities, almost every infrastructure, i.e., energy, health, building, environmental, public safety, and transportation, is controlled and monitored using smart technologies like sensors, CCTV cameras, and other devices (Rosati, U., & Conti, S., 2016). Internet of things (IoT) (Al-Garadi, M. A., et al., 2020) is an idea that covers the overall system of a smart city monitored and controlled. A recent model has been proposed especially for smart cities in which a smartphone reads the different values like sound, pressure, speed, and Gravitational force (G-force) while traveling in a vehicle. If the accident happens, it sends the location and values of data to the cloud, which saves the received information to the database, which will inform the nearest hospital in its database about the misfortune plus the position of the vehicle, then the hospital conducts the ambulance towards the location (Bhatti, F., Shah, M. A., Maple, C., & Islam, S. U., 2019).

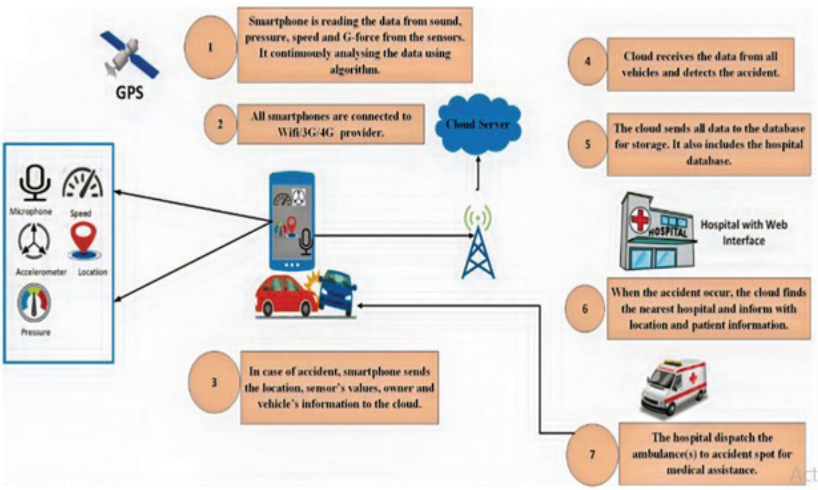

Fig. 3. Elaboration of the smartphone-based misfortune uncovering approach (Bhatti, F., Shah, M. A., Maple, C., & Islam, S. U., 2019).

Figure 3 shows the complete procedure of smartphone-based mishap uncovering in which the smartphone sends the location and readings of several values like speed, sound, pressure, etc., to the cloud server, which will find the nearest hospital from its database and inform that hospital about the mishap. The hospital will then send the medical aid to the mishap location. Classification of vehicles is a popular and useful field for Intelligent Transport System (ITS). Recognizing vehicles is helpful for traffic policymakers, public safety organizations and insurance companies, etc. it can automate the process of toll collection, pollution estimation, and traffic modeling. The systems dependent on computer vision methods make a robust approach for understanding and getting information (Bansal, A., Aggarwal, N., Vij, D., & Sharma, A., 2018, May).

3. Classification of Accidental and Non-accidental Vehicles

Classification of accidental and non-accidental vehicle images is used for training the robots and can be used in smart city concepts to handle such emergencies. The existing works applied feature extraction approaches like Histogram of Gradient (HOG) (Sulistyaningrum, D. R., et al., 2020, March), Speeded-Up Robust Features (SURF) (Das, R., Kumari, K., De, S., Manjhi, P. K., & Thepade, S., 2021), Local Binary Pattern (LBP) (Tuncer, T., & Dogan, S., 2020), and Maximally Stable Extremal Regions (MSER) are deliberated initially but, they are not best for analyzing accidents. While

Convolutional Neural Network (CNN) (Fang, L., Zhang, H., Zhou, J., & Wang, X., 2020) is known as the most suitable method for handling images covering the latest research (Juliet, S. E., Sadasivam, V., & Florinabel, D. J., 2014). Vehicle tracking using onboard image capturing devices gets more attention from scientific and business authorities due to accidents that happen by vehicles (Arróspide, J., Salgado, L., & Nieto, M., 2012).

4. The Problem that Can be Faced in Computer Vision-based Automated Accident Analysis

In image processing, the detection of accidents comprises four chief phases: feature optimization, classification, feature extraction, and feature fusion. However, some challenges may decrease the system's accuracy, as mentioned below.

• There may come an issue of occlusion (Lazarow, J., Lee, K., Shi, K., & Tu, Z., 2020) while classifying the dataset images of vehicles, as in some images, there are other vehicles in front or beside the targeted vehicle, which may cause confusion or difficulty in classification.

• Illumination (Zeng, Z., et al., 2020) is also a factor that may create difficulty during the classification of vehicle images, as in our different datasets, images are taken at different timings in different weather conditions; therefore, in some images, there is an excess amount of light or reflection of light which made image unclear.

• Rotation of images causes much difference as in some cases, if the image is rotated, it may look like the vehicle is inverted. This will make confusion about inter and intraclass variation.

5. Contributions to Road Accidents Analysis and Responses

As the vehicles assisted man in traveling from one place to another place in a short time compared to without vehicles, most people are buying their private vehicles for their personal use. Buying more and more vehicles causes an increase in traffic burden on roads which is also a reason for increasing traffic accidents. When an accident happens, people get injured badly and die later due to emergency medical services not being given on time. As human lives are very important, different techniques are proposed to decrease the death ratio due to late medical services. Misfortune exposure plus its administration are glowing inspected, plus several scholars have conducted the revisions towards creating misfortune uncovering supplementary unfailing plus proficiency (Khaliq, K. A., et al., 2018). Research is done based on vehicle classification in which authors have explored the possibility of consuming CNN features on behalf of automobile sorting using the science of sound. A modest CNN is deliberated for the mining of structures from auditory tapes occupied commencing the automobile. Automobiles are categorized into five main classes, i.e., bus, train, plane, three-wheeler, and car employing support vector machine (SVM) (Bansal, A., Aggarwal, N., Vij, D., & Sharma, A., 2018, May). Similarly, the internet of things (IoT) has been a rapidly upcoming field in the last few years with the up-gradation in many different implantation fields like in the army, navy, intelligent transportation, smart health, smart grid, smart home, and smart city areas. A system is developed which is intelligent in detecting accidents that happen in traffic in which microscopic variables of vehicles are exchanged with each other. The introduced system uses simulated data provided by the vehicular ad-hoc network (VANETs) (Malhi, A. K., Batra, S., & Pannu, H. S., 2020), dependent on the speeds plus coordinates of the vehicles, and then a traffic alert is sent to the drivers (Dogru, N., & Subasi, A., 2018, February). A bottomless erudition scheme is developed for feature mining by employing the fusion of cataloging professionals by taking the accident images. For the startup step, the results of the last max-pooling layer of CNN are consumed in the direction of extracting the concealed topographies mechanically. Intended for the next step, a concoction of innovative dissimilarities of extreme learning machine (ELM) (Wu, L., et al., 2020) including on-line sequential ELM (OSELM) (Sahani, M., Dash, P. K., & Samal, D., 2020), kernel ELM (KELM) (Afzal, A. L., Nair, N. K., & Asharaf, S., 2021), basic ELM (Zhang, W., Han, D., Li, K. C., & Massetto, F. I., 2020), and constraint ELM (CELM) (Zhang, W., Han, D., Li, K. C., & Massetto, F. I., 2020; Jing, S., & Yang, L., 2020) is industrialized (Juliet, S. E., Sadasivam, V., & Florinabel, D. J., 2014). Different approaches and techniques are proposed for ITS (Salisu, U. O., et al., 2020) and smart city concepts to decrease the number of demises because of roadside misfortunes. In European countries, an Emergency Call (eCall) system is installed in all the latest vehicles, which would detect an accident and will send messages to relevant emergency services through a duplex communication channel (Lupinska-Dubicka, A., et al., 2020). Cameras mounted on the roads are also a very vital source of information regarding traffic activities. Data-driven from those cameras can be used for risk prediction regarding traffic accidents. An integrated two-stream convolutional network design is proposed, which accomplishes instantaneous uncovering, tracing, and nearby-mishap uncovering of thoroughfare consumers in circulation statistics gained by cameras installed on roads (Huang, X., He, P., Rangarajan, A., & Ranka, S., 2020). In America, streetlights are also used for the detection of vehicle accidents; an audio sensor is installed with the streetlight, which is designed to generate an electrical signal on detecting a sound, a controller is also attached to the street light which will decide whether the sound is produced by any vehicular accident. Streetlight also contains a light source connected to provide a visual notification of vehicular accidents in response to the controller for confirmation. Then the controller will send the signal to the nearest emergency response Centre (Cho, N. C., & Joshi, P., 2020). As in most of the proposed accident detection approaches, the internet and communication must be there to work those proposed methods. However, a blockchain-based accident detection method is introduced, also known as offline detection, used for accident detection in the absence of internet and communication (Davydov, V., & Bezzateev, S., 2020, January). In developing countries, radars are also installed on the roads for data collection like rapidity, device occupancy, and volume. Based on these statistics, the feasibility of bottomless erudition mockups is explored to uncover accidents and predict accident risk. There may be bad weather conditions like rain or fog when an accident happens; it would be complicated for the detection system to identify the misfortune and inform the relevant response facilities. Therefore, to overcome this issue, vision-based accident detection architecture is introduced to quickly detect accidents in poor weather conditions like rain, fog, and night with low lights. In this proposed model retinex image enhancement algorithm and you only look once (YOLO) v3 (Zhao, L., & Li, S., 2020) model is used for improving the quality of images and for different object detection, which will help in accident detection (Wang, C., Dai, Y., Zhou, W., & Geng, Y., 2020). Figure 4 represents the vision-grounded mishap uncovering approach designed especially for bad weather conditions.

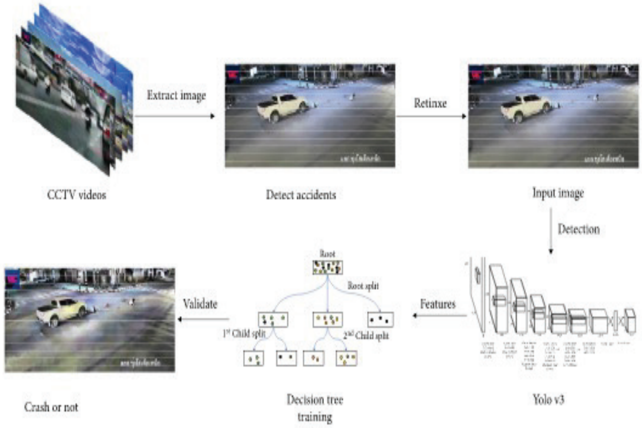

Fig. 4. Vision-based accident detection architecture (Wang, C., Dai, Y., Zhou, W., & Geng, Y., 2020)

In some developing countries, projects were built in which there is a sensor installed in the vehicle, which will direct an indication towards the microcontroller to detect an accident. A global system for mobile communication (GSM) (Ashwini Kumari, P., & Geethanjali, P., 2020) module is likewise there, which will help the microcontroller inform the police or rescue services and the relatives of the fatality about the accident and its location. If, luckily, the passengers of vehicles survived and did not need medical aid, they can cancel the process of informing the emergency teams by pressing a button present in the vehicle (Jebril, N.A., et al., 2017; Prabha, C., Sunitha, R., & Anitha, R., 2014; Sanathra, M., et al., 2019); in some approaches, confirmation is done through

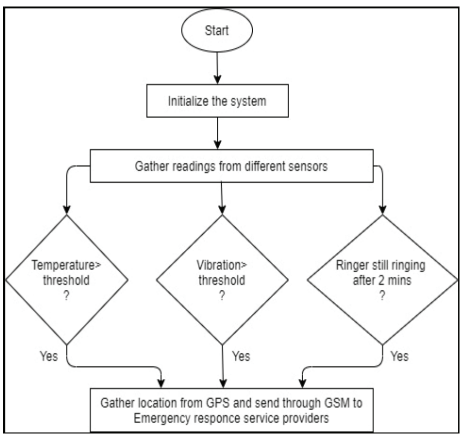

Fig. 5. Flowchart explaining the sensor-based ringer architecture for misfortune uncovering (Bangare, P. S., et al., 2019)

an android app on driver's smartphone (Sanathra, M., et al., 2019). Another system is designed with different sensors and microcontrollers installed in the vehicle, which will produce a ringer sound for two minutes after the accident detection, and if the driver did not stop that ringer sound, then an alert would be sent to emergency centers. In this system, accident severity is observed first, and aid is sent accordingly (Bangare, P. S., et al., 2019). Figure 5 shows the complete flow of this sensor-grounded ringer approach.

An American patent is developed in which such a system is suggested to detect the crash through mobile devices and sensors installed within the automobiles. Damages and causalities are estimated using smartphones, and according to that causality rate, nearest or relevant emergency service providing points are informed (Fernandes, B., et al., 2016). Another rapid system is developed in which there should be a smartphone, which will make an ecall to the emergency respondent person on detecting the crash, and medical service would be sent to the crash site immediately (Fernandes, B., et al., 2016).

With the excess use of smartphones in our daily lives, research scholars are now using smartphone technologies for the well-being of mankind. Now smartphones are used to help the people in causalities like affected people at road crash sites. With the combination of smartphone and IoT (Fernandes, B., et al., 2016), architecture is developed in which there are sensors in the smartphone that will notify and show the vehicle's location to the public safety organization (PSO) when the crash is detected. As the PSO already has the details of passengers like name, blood group, and when the vehicle is registered with them, therefore quick first aid would be sent accordingly to the crash location after getting the location of the crash through the global positioning system (GPS) (Li, C., Fu, Y., Yu, F. R., Luan, T. H., & Zhang, Y., 2020; Nasr, E., Kfoury, E., & Khoury, D., 2016, November). In this approach, an IoT device is installed in an automobile with GPS, and a shock-sensor will detect the mishap, and the smartphone will send the passenger_id and automobile_id along with location to the server. Mostly the approaches are introduced for the accident detection of four-wheel automobiles. At the same time, a smart helmet named konnect is developed for two-wheel automobiles, which will use the processor, having enabled wireless fidelity (Wi-Fi) processor and cloud computing substructure to detect and inform medical service providers about the crash (Chandran, S., Chandrasekar, S., & Elizabeth, N. E., 2016, December). An automatic crash detection architecture is developed, grounded on computational intelligence techniques. Experiments are performed on data gathered from Istanbul highway sensor readings and traffic databases. Big data processing approaches are used to process data (Ozbayoglu, M., Kucukayan, G., & Dogdu, E., 2016, December). Video data obtained from cameras mounted on roads can also be very helpful in developing a system for crash recognition. A prophecy-grounded road crash recognition procedure for thoroughfares plus superhighways is planned. The suggested process is grounded on a malleable transportation gesture movement demonstrating practice, farneback photosensitive movement for gesture recognition, and a statistic investigative scheme for crash recognition (Maaloul, B., et al., 2017, June). A unique process grounded on ELM (Hai, T., et al., 2020) is proposed, named OF-SIFT is consumed as the low-level feature for detecting accidents by using traffic video data (Chen, Y., Yu, Y., & Li, T., 2016, August). Another smart helmet is introduced for two-wheeler automobile users who have very interesting features that ignition will not be on while waiting for the motorist not putting on the head covering, and his breaths are non-alcoholic. Besides these features, it also can detect the accident and inform the medical service providers about the location of the crash by using the technology of GSM (Selvathi, D., Pavithra, P., & Preethi, T., 2017, June). A crash detection system is proposed in which the impact interval grouping (IIG) algorithm is utilized to recognize roadside crashes by classifying the spatiotemporal patterns in roadside movement promptness statistics. Multivariate time series (MTS) (Bianchi, F. M., Scardapane, S., Løkse, S., & Jenssen, R., 2020) is also proposed as a classifying approach for the measurement of roadside crash severity (Yue, M., Fan, L., & Shahabi, C., 2018, June). The blockchain-grounded crash recognition approach is introduced named as offline-detection. This proposed architecture will work without the internet and communication (Davydov, V., & Bezzateev, S., 2020, January). A supervised learning approach is proposed, which classifies that either the vehicle in the image is crashed or not. A dataset consisting of two classes, accidental vehicle images class, and non-accidental vehicle images class, is used to train the proposed approach (Liao, C., Shou, G., Liu, Y., Hu, Y., & Guo, Z., 2017, December). An atmega328P controller is designed to visualize and monitor the accessible areas in the system. If an accident happens in those areas, the designed controller will automatically detect and inform relevant authorities (John, A., & Nishanth, P. R., 2017, April).

5.1. Accident Detection

Different accident detection approaches have been introduced to reduce the number of misfortunes happening on roads, plus the mortality ratio increased due to those accidents. As the real-time detection of accidents is a key point of any proposed system, an approach is introduced in which an onboard eCall device is installed in the vehicles, which will inform emergency service providing authorities on detecting an accident (Lupinska-Dubicka, A., et al., 2020). Nowadays, almost everyone has a smartphone with fast internet every time; therefore, researchers are focused on using smartphone technologies to detect and inform about accidents (Aung, N. W., & Thein, T. L. L., 2020, February). Installation of cameras on roads is a common practice now; therefore, data obtained from those cameras can also be used for crash detection; an architecture is proposed in which an integrated two-stream CNN is used for quick crash detection by using video data obtained from roadside cameras (Huang, X., He, P., Rangarajan, A., & Ranka, S., 2020). In almost all of them so far, proposed methodologies of an accident detection, internet, and communication are the two factors that must be there for the working of that proposed methodology, but there is an approach based on blockchain which will detect the crash without internet and communication (Davydov, V., & Bezzateev, S., 2020, January). A Machine learning (ML) (Barros, D., et al., 2020) technique named eXtreme Gradient Boosting (XGBoost) (Yu, B., et al., 2020) is used for the fast detection of an accident (Parsa, A. B., et al., 2020).

5.2. Preprocessing

Preprocessing is the foremost step in registering the images for the machine learning pipeline. There can be different preprocessing steps in image processing such as: noise removal (Sharif, M., Irum, I., Yasmin, M., & Raza, M., 2017; Irum, I., Shahid, M. A., Sharif, M., & Raza, M., 2015; Irum, I., Shahid, M. A., Sharif, M., & Raza, M., 2015; Irum, I., Shahid, M. A., Sharif, M., & Raza, M., 2015; Irum, I., Sharif, M., Raza, M., & Yasmin, M., 2014), reconstruction (Abbas, F., et al., 2021), contrast enhancement (Irum, I., Sharif, M., Yasmin, M., Raza, M., & Azam, F., 2014; Shah, G. A., et al., 2015) illumination normalization (Hussain Shah, J., et al., 2015; Sharif, M., Mohsin, S., Jamal, M. J., & Raza, M., 2010, July) and segmentation (Masood, S., et al., 2015).

In-vehicle accident detection, different pre-processing techniques are used to make images more refined and fast detection. In an accident recognition technique, the background removal approach is used to recognize accidents (Cho, N. C., & Joshi, P., 2020) quickly. As driver's carelessness is the leading cause of accidents in most cases, a system is designed for examining the driver's situation at the time of driving, in which infrared night vision cameras are used for image acquisition. As a pre-processing approach, noise is removed from the images and converted into binary images by using a specific threshold for better and quick observation to prevent the risk of an accident (Ao, S. I., Rieger, B. B., & Chen, S. S., 2008). Conversion of red, green blue (RGB) (images to grayscale images is also a commonly used pre-processing technique. In a proposed model for detecting anomalies on roads to prevent the risk of a road crash, images gained through roadside cameras are converted into grayscale images for quick object detection, but the object recognition quality is not good (Makhmutova, A., et al., 2019, October). Pre-processing is used in systems where sensors gather data about the driver's behavior while driving to remove noise from sensors (Van Nguyen, T., et al., 2020).

5.3. Features Extraction

Feature extraction is a very vital step towards classification (Amin, J., et al., 2022; Fayyaz, A. M., et al., 2022). Different approaches to feature extraction give different results; in the case of detection of the accident, extraction of features matters a lot. It is used to evolve and analyze the input or original image to find and resolve the required issue. Features extraction is of three main types, which are handcrafted (Saba, T., et al., 2021; Naz, J., et al., 2021; Sharif, M., et al., 2020; Fayyaz, M., Yasmin, M., Sharif, M., & Raza, M., 2021; Sharif, M., et al., 2019, April; Rehman, M., Sharif, M., & Raza, M., 2016), deep features (Saba, T., et al., 2021; Nasir, I. M., et al., 2022; Alkinani, M. H., et al., 2022; Shahzad, A., et al., 2021; Saba, T., et al., 2021; Naz, M., et al., 2021; Ramzan, M., et al., 2021; Amin, J., et al., 2021; Amin, J., et al., 2020; Amin, J., et al., 2020a; Fayyaz, M., et al., 2020; Raza, M., et al., 2017, August), and an amalgam of both (Naz, J., et al., 2021; Saba, T., et al., 2018). Shape (histogram oriented gradient (HOG)) (Isola, P., Xiao, J., Torralba, A., & Oliva, A., 2011, June), texture, and color features (color transformation) (Bay, H., Ess, A., Tuytelaars, T., & Van Gool, L., 2008) are the most commonly used feature descriptors of handcrafted type. A bottomless erudition scheme is developed intended for feature mining and the fusion of having classification professionals by taking the accident images (Juliet, S. E., Sadasivam, V., & Florinabel, D. J., 2014). Deep features consist of Local and global features, including

AlexNet and ResNet.

5.4. Feature Selection

Good research practices recommend that the feature selection (FS) be made after the extraction of features so that the most suitable and revealing features should be acquired (Sharif, M. I., et al., 2021; Khan, M. A., et al., 2020; Khan, M. A., et al., 2021; Khan, M. A., et al., 2020). Six feature selection approaches are used in architecture for the classification of accidents (Hadjidimitriou, N. S., et al., 2019), in which Pearson correlation (Pearson, K., 1895), Chi-2 (Pearson, K., 1900), makes the selection of features depending upon a threshold assessment implemented in the direction of the expected coefficients of the logistics regression (Pedregosa, F., et al., 2011). For the finding of an essential factor of mobile advertisement, a feature assortment technique named most minor absolute shrinkage and selection operator (LASSO) (Kukreja, S. L., Löfberg, J., & Brenner, M. J., 2006) is utilized (Chun-Cheng, L., & Goutam, C., 2016). Performance may be affected by using vast features as employing the upsurge in the number of structures; the training phase would increase. An upsurge in the number of structures may become the reason for overfitting. For detecting an accident, in a proposed architecture, algorithms of feature selection implemented are feature importance, univariate feature selection, and recursive feature elimination (Labib, M. F., et al., 2019, June). A new technique named correlation-based feature selection (CFS) (Cahyani, N., & Muslim, M. A., 2020) stands to be used for the selection of features in the direction of obtaining the maximum results in accident detection and reporting (Polepally, V., & Shahu Chatrapati, K., 2019). An automatic feature selection approach is introduced, in which features are ranked according to their importance (Cano, G., et al., 2017).

5.5. Feature Fusion

Feature fusion is an essential step in computer vision and image processing (Sharif, M., et al., 2020; Khan, M. A., et al., 2020; Nisa, M., et al., 2020; Khan, M. A., et al., 2019; Rashid, M., et al., 2019; Amin, J., Sharif, M., Raza, M., & Yasmin, M., 2018; Zahid, M., et al., 2021) as it is to be decided which features should be fused so that maximum result should be achieved. There are two types of feature fusion one is serial fusion and the other is parallel fusion. Feature fusion is done since the characteristics lacking in one feature would be covered by fusing it with other features; hence, the maximum results are achieved compared to individual ones. An architecture named single shot multibox detector (SSD) (Thakkar, Y., et al., 2020) be there introduced aimed at the fast detection of accidents and minor items; in this architecture, multi-scale feature fusion is implemented in which several levels of feature maps are fused (Jiang, H., Wang, Y., & Yang, Y., 2019, October). A cataloging technique of adaptive concerned area grounded on a novel detection procedure of crash automobiles grounded upon multi-feature merging is suggested to categorize the thoroughfare hindrances (Lan, J., et al., 2016). A novel multiclass unusual driving manners appreciation technique is proposed in which, as an initial step, basic features like texture, color, and gradient direction are extracted, then covariance and manifold description maps are used, and multi-feature fusion is accomplished (Cijun, L., & Yunpeng, L., 2019). An object tracking approach is suggested in which multi-channel feature fusion is used, which focuses on fusing several channel features into a highly expressive one, in which the associations between diverse feature channels can be optimally consumed (Huang, K., et al., 2020). Scholars have established a novel stacked random forests-feature fusion (SRF-FF) (Huang, K., et al., 2020) practice to pinpoint breakages in numerous areas similar to an arm, lower leg, knee, ankle, foot, and hand (Joshi, D., & Singh, T. P., 2020). Prediction of drug pills is also made using multi-scale feature fusion (Chang, W. J., et al., 2020). An appropriate fusion practice must have these possessions a) Consequential fused image should retain all consistent and worthwhile data of input image, b) Combination procedures should be gripping to some unpredictable circumstances, and c) these approaches do not carry any pictorial items that can distress the unvarying surveillance and additional processing like categorization (Li, S., et al., 2017). A combination of numerous data in one trajectory remains one of the developing approaches in computer vision and machine learning grounded on their numerous implementations (Sharif, M., et al., 2020). The most important objective of feature blending is to syndicate the robust and discriminative data of wholly mined structures in individual trajectories to improve performance and enhance the structure accomplishment period (Fernandes, S. L., & Bala, G. J., 2016).

6. Datasets

There must be a dataset based on which proposed approaches are implemented, and results are observed in accident detection or classification. Researchers used several datasets, some made their datasets, and some were collected from different organizations. In a proposed near accident detection architecture, a traffic near-accident detection dataset (TNAD) made from the video data collected from cameras installed on roadsides is used for experimental purposes (Huang, X., He, P., Rangarajan, A., & Ranka, S., 2020). A quick crash recognition approach is suggested, whose verification is done by implementing that approach on a dataset gathered from the Illinois department of transportation (IDOT) (Parsa, A. B., et al., 2020). For instance, in computer vision plus image processing, vehicle images are also used to identify the license number plate of vehicles. A similar architecture is designed to detect license number plates of automobiles quickly. A vehicular dataset named Caltech car dataset contains 526 images and 101 classes, and a locally made dataset by the researchers is used for the performance of experiments to validate their results. Datasets are made in different ways; some researchers gather their required dataset from different organizations or companies, while some would prefer to make their dataset on which they would have a plus point that would be their dataset, and no work has been done that dataset before. There is another way of dataset increment, known as dataset augmentation, in which rotation of images is done at different angles to increase the number of images. Another off-the-shelf CNN structure grounded tactic intended for automobile sorting (Bansal, A., Aggarwal, N., Vij, D., & Sharma, A., 2018, May) uses a dataset of 4789 recordings each of about 30 seconds. In an automobiles detection approach, three different datasets named 1) GTI (Laopracha, N., Sunat, K., & Chiewchanwattana, S., 2019), composed of 7000 images divided into four classes, 2) CompCars (Yang, L., Luo, P., Change Loy, C., & Tang, X., 2015), which consists of 164344 images and two classes; and 3) KITTI (Geiger, A., Lenz, P., & Urtasun, R., 2012, June), are used for the validation of proposed architecture (Laopracha, N., Sunat, K., & Chiewchanwattana, S., 2019).

7. Conclusion

The number of vehicles on the roads is increasing day by day, which causes an increase in the accident ratio. Therefore, efforts are made to minimize the ratio of accidents. Numerous studies are presented in the existing literature to tackle accidents situations. This work represents an overview of the state-of-the-art approaches to automatically studying traffic accidents. The prominent tools and techniques adopted by the researchers include using IoTs, smart sensors, and machine learning (especially computer vision). This work will be helpful to the researchers and developers in searching the new avenues in automated road accidents analysis.

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