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Car Crash Detection System using Machine Learning and Deep Learning Algorithms

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Abstract: Over 80% of mishaps are caused by a lack of identifying the accident on time, as well as failure to arrive in time to provide emergency care for the victim. The point is to distinguish and utilize machine learning to decide the best means of detecting car crash with light of the live transfer of dash cam data in the vehicle. The thought is to take every pixel and run it with a deep learning model prepared to recognize video outlines into mishap or non-mishap. Essentially, in Artificial Intelligence (AI), informational indexes are collected. Gathered information bases will be refined and given to AI calculations to prepare for image recognition with the help of computer vision. After fruitful preparation, AI calculations will be tried and the outcomes will be recorded for examination purposes. In the proposed vehicle crash location framework, the impact identification is performed utilizing the Convolutional Neural Network (CNN), taking a bunch of pictures as information, the framework distinguishes the crash, the effect of the vehicle and the greatness of the mishap. Based on the performance of machine learning algorithms, comparative analysis is performed and the results will be tabulated. Two machine learning algorithms are considered i.e. Random Forest Classifier and Logistic Regression which enables the output regarding the generated index from the CNN and running through the indices with location impact and severity of the damage.

Keywords: Machine Learning, Deep Learning, Dash Camera, Logistic Regression, Random Forest, Convolution Neural Network.

I. INTRODUCTION

According to the World Health Organization (WHO), the severity of road traffic accidents (RTCs) is a key component in assessing and resolving welfare losses. Accidents on the road are a major source of concern for everyone. Every day, a great number of precious lives are lost as a result of car accidents. Given the high incidence of fatalities associated with street collisions, it is a critical field that requires extensive research. Weather conditions, road types, light conditions, etc. are answerable for such events. Lots of injuries take place and reporting the coincidence as quickly as possible is a great deal necessary.

In the proposed automobile crash detection system, the detection of automobile crashes is accomplished by the usage of CNN and the system similarly compares the prediction of a sample of injuries against Logistic Regression (LR) and Random Forest (RF) algorithms concurrently, along with the influence of significant variables on accuracy, sensitivity, and specificity. It then explores the most appropriate integrated method, and selects appropriate input variables for classifying road crash severity and the effect of the automobile crash. In this case the proposed system enables a fast reaction to automobile injuries and efficient management of traffic flow. In this project, the aim is to identify the best algorithm for detecting car crashes among machine learning algorithms, in addition to detection using deep learning algorithms. In machine learning, Logistic Regression is compared with Random Forest; likewise, in deep learning, a Convolutional Neural Network is used. These are the three algorithms commonly used in the literature. In addition, technical papers related to auto accident detection were reviewed to gain knowledge of previous work done in the field, providing a clear idea of the algorithms involved in this proposed project.

II. LITERATURE REVIEW AND THEORETICAL FOUNDATIONS

Previous work reviewed in the reference documents covers image-based damaged-vehicle recognition, video-based accident detection, accident-prone-area analysis, and deep-learning approaches for road-event recognition. Ravindran et al. described a machine-vision method for identifying damaged vehicles from images, using a staged scanning process to classify an image as containing a damaged vehicle. Ghosh et al. investigated accident detection from camera footage using CNNs, with the objective of identifying an accident rapidly and sending information to relevant authorities.

Gaurav et al. examined accident detection, severity prediction, and accident-prone-area identification using image segmentation, machine learning, and sensors. The reference paper reports a 95 percent accuracy figure for its linear-regression-based prediction task.

Other cited studies include work on traffic accident severity prediction with deep neural networks, IoT-based automatic accident detection, spatial simulation for emergency-service planning, machine-learning approaches to video recordings, random-forest traffic accident detection, fast car-crash detection in video, and vehicle-accident classification using deep convolutional neural networks.

From a theoretical perspective, CNNs form the principal deep-learning component of the system. A convolutional layer applies learned filters over local image regions and produces feature maps. Pooling reduces spatial dimensions and computational complexity while retaining prominent features. Fully connected layers use the extracted representation for classification, while dropout can be used as a regularization mechanism to reduce overfitting. These operations allow the model to progress from low-level visual patterns toward higher-level representations relevant to accident recognition.

The source report also discusses VGG-16 as a transfer-learning foundation for damaged-vehicle classification. Because the original pretrained model does not directly provide a damaged-vehicle class, an additional classifier is trained on top of the learned representation. The resulting pipeline can be organized into vehicle identification, damage classification, impact-location estimation, and severity assessment.

Random Forest provides a complementary machine-learning perspective through ensemble learning: multiple decision trees are combined to obtain a classification or prediction. Logistic Regression provides a comparatively simple statistical classification baseline. In the proposed workflow, these conventional classifiers operate on processed or annotated information to predict crash-related patterns, while the CNN performs visual recognition.

III. THE PROPOSED MODEL

As the number of vehicles increases every day, the risk of accidents rises directly with it. This project will immensely benefit people by providing insight into the estimation of a car crash and how the impact and severity, together with location assessment, can render a quote to determine the cost of repair. It also informs the owner about the approximate cost by considering deep learning with a suitable algorithm to detect the impact of the crash, recording the annotation in text format and thereby creating a dataset for the car crash.

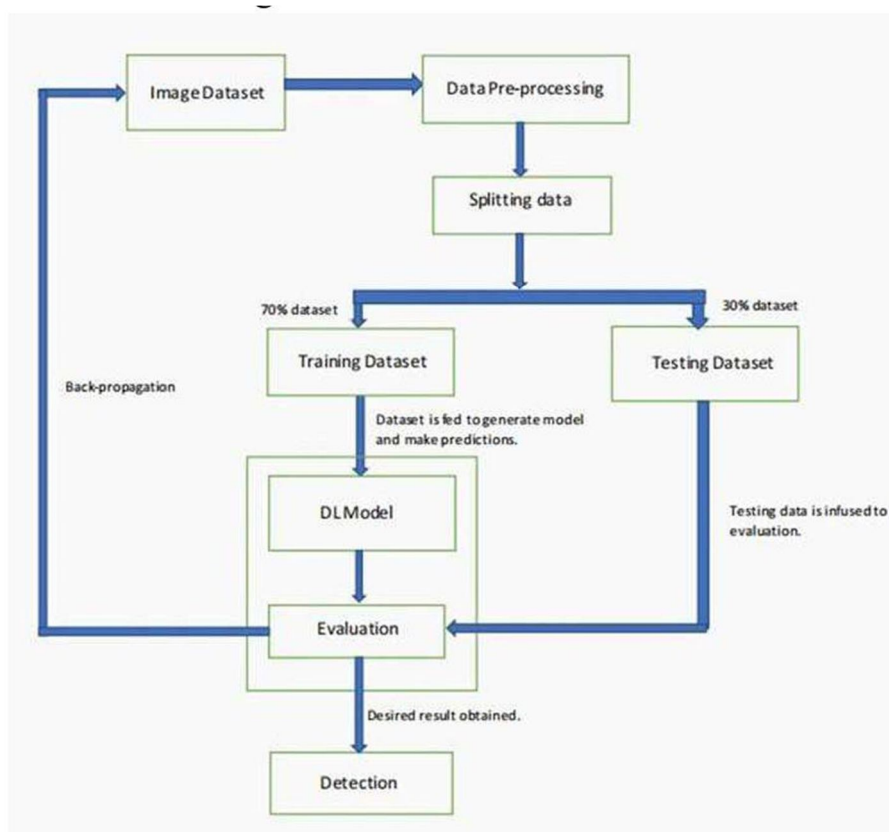


Fig. 1 Representation of deep learning for image dataset

As illustrated in Fig. 1, an image dataset formed from the frames of the car crash detection dataset is selected and preprocessed by checking whether the image is of a car or not, and the information is stored in the classifier using pickle. The individual image is then categorized and segregated by first point of impact and severity of the damage, and stored accordingly in their respective classifiers. A method is used to access and utilize the stored data in the classifier, thereby allocating the image with a proper estimation to evaluate the impact of the car crash.

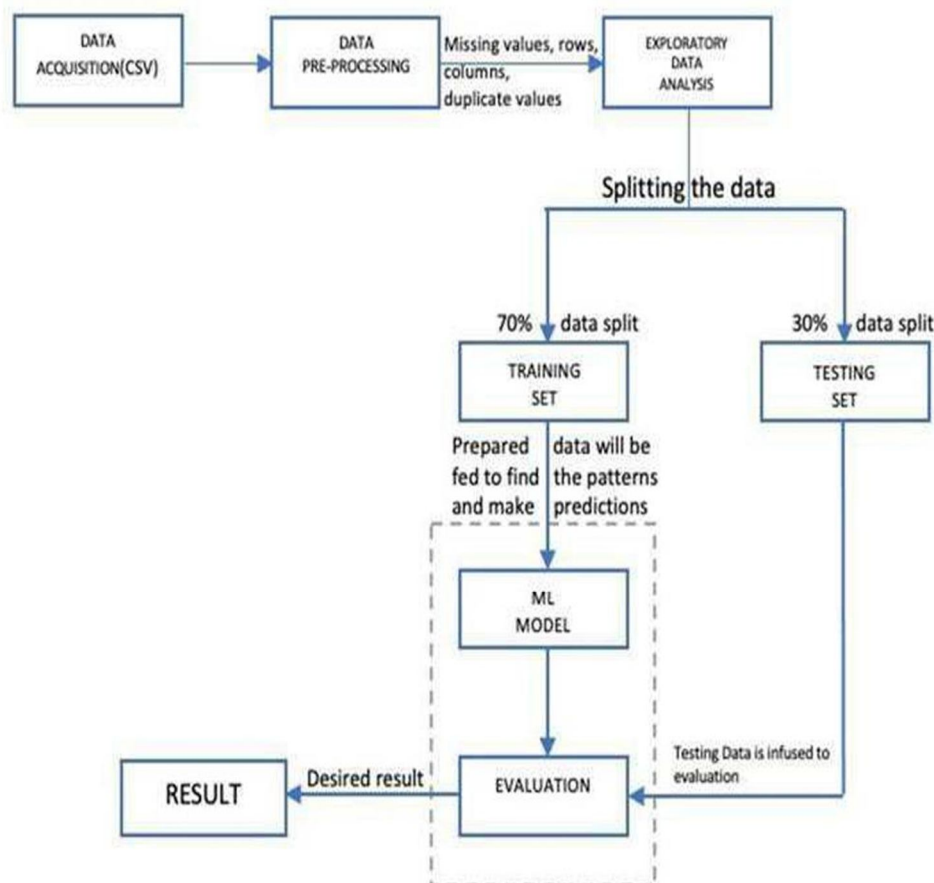


Fig. 2 Representation of the machine learning process

As shown in Fig. 2, the stored data, annotated into text format, is run through two machine learning algorithms that are more suitable for faster output to determine whether the impact and location assessment can be modelled to obtain a suitable estimation of the car crash, thereby helping the insurance company make a faster judgement on the impact of the crash.

IV. METHODOLOGY

The methodology is organized as a sequence of data acquisition, preprocessing, visual classification, feature/label generation, machine-learning prediction, and notification. The reference material describes both dash-camera and CCTV video as possible sources. Frames are extracted from the video stream and prepared for model processing.

A. Data Acquisition and Preprocessing

An image dataset is formed from frames associated with car-crash detection. The images are inspected to determine whether they contain a vehicle and are then organized for subsequent classification. The reference project states that annotations are stored in text form and that images are separated according to the first point of impact and severity of damage. For tabular accident data, the project describes loading the dataset into Google Colab, examining anomalies, removing unnecessary columns, handling missing and duplicate values, and reducing an initial 70-column dataset to 19 relevant columns.

B. CNN-Based Detection

The CNN receives image frames and extracts spatial features through convolutional filters. Pooling operations reduce the feature-map dimensions, and the resulting representation is passed to classification layers. The system uses the learned representation to distinguish accident-related visual patterns from normal road or vehicle scenes. The broader report also describes a real-time CCTV workflow in which frames are analysed continuously.

C. Impact and Severity Classification

After the vehicle and damage-related information is obtained, the image is categorized according to the point of impact and severity. The reference paper describes storing these categories in classifiers so that a new image can be assigned an estimated crash state. This provides information beyond a simple binary accident/non-accident decision.

D. Random Forest and Logistic Regression

Two conventional machine-learning models are considered for comparative prediction. Random Forest combines multiple decision trees through ensemble learning, whereas Logistic Regression models the relationship between input variables and a classification outcome. The project uses these models to examine crash-related patterns such as severity and impact location after the visual information has been processed.

E. Alert and Emergency Notification

The reference implementation includes a notification workflow capable of sending accident information to relevant recipients. The broader project report describes SMS and email-style notification containing an accident message, timestamp, and geographic information, with the intended recipients including nearby hospitals and police stations. This component connects the recognition model with the response stage of the accident-management process.

F. Development Environment

Python is used as the primary programming language. The source material identifies Google Colab as an interactive environment for executing Python and using GPU resources. The larger project report also lists tools and libraries including OpenCV, TensorFlow, Keras, NumPy, Pandas, Pillow, PyTorch, Django, Pusher, and Vonage.

V. RESULTS AND DISCUSSION

The reference paper presents the system as a comparative framework rather than providing a complete set of numerical test results for every classifier. Its conclusion states that CNN is used to confirm an accident and identify severity and point of impact from video data, while Random Forest and Logistic Regression are used to predict accident patterns with respect to severity and impact location. The associated project report additionally describes real-time accident detection from surveillance video and an alert mechanism for emergency response. The literature summarized in the sources provides several quantitative reference points. One cited study on automatic car-accident detection based on cooperative vehicle-infrastructure systems reported detection in 0.0461 seconds (21.6 FPS) with 90.02% average precision. The supplied conference paper also reports a 95% accuracy figure for the linear-regression-based accident prediction task described by Gaurav et al. These values belong to the cited studies and should not be interpreted as measured performance of the present implementation. Qualitatively, the combined workflow offers three levels of analysis: visual accident confirmation through CNN, structured prediction of crash characteristics through conventional classifiers, and operational response through notification. The use of image and video data avoids dependence on installing a dedicated physical sensor in every vehicle, although the approach remains dependent on camera availability and image quality.

An important observation is that accident detection and accident-severity estimation are related but distinct tasks. A frame can provide evidence that a collision occurred, while additional information is required to determine the location and magnitude of damage. Separating these stages makes the architecture easier to extend and allows different classifiers to be evaluated for different prediction tasks.

VI. LIMITATIONS

First, the source materials do not provide a complete standardized experimental protocol containing dataset size, train/validation/test split, class distribution, or a full confusion matrix. Consequently, a precise independent performance comparison among CNN, Random Forest, and Logistic Regression cannot be established from the supplied documents alone.

Second, camera-based detection is affected by environmental and acquisition conditions. Weather, lighting, camera angle, occlusion, image resolution, traffic density, and motion blur can alter the visual appearance of an accident. The reference report identifies weather, road type, and lighting as factors associated with road accidents, but the supplied documents do not report systematic experiments across these conditions.

Third, real-time deployment requires sufficient computational resources and stable video processing. The project report lists a development configuration containing an Intel Core i5 processor, 8 GB RAM, 1 TB storage, Windows 11, and an NVIDIA GeForce GTX 1660 Ti GPU; this indicates the type of environment used for development but does not establish the hardware requirement for all deployment scenarios.

Finally, notification accuracy depends on the correctness of location and contact information. A false positive could trigger an unnecessary response, while a false negative could delay assistance. Therefore, operational deployment requires additional validation, monitoring, and safeguards before being relied upon for emergency response.

VII. CONCLUSION AND FUTURE SCOPE

This work presents a computer-vision-based framework for car-crash detection using machine learning and deep learning. The approach uses CNNs to analyze visual data and distinguish accident-related frames, while Random Forest and Logistic Regression provide additional prediction of crash characteristics such as impact location and severity. The source project further connects detection with real-time notification to emergency stakeholders. The overall workflow demonstrates how visual recognition can be integrated with structured machine learning and an alert mechanism for faster incident reporting.

The supplied project report indicates that experimentation was carried out using images and that the proposed approach is intended for deployment on surveillance cameras. However, the conference version should report only experimentally measured values that are available from the actual implementation. Additional controlled evaluation is therefore needed to establish robust performance across datasets and road conditions.

Future development can extend the system toward integrated CCTV and roadside monitoring, GPS-based location services, GSM or other communication modules, number-plate identification, driver-behavior or alcohol-related risk detection, and centralized emergency coordination. The source report also proposes extending the system beyond detection toward victim assistance and preventive alerts. Further work can investigate larger and more diverse video datasets, temporal video models, edge-device deployment, improved severity estimation, false-alarm reduction, and systematic evaluation using precision, recall, F1-score, sensitivity, specificity, latency, and frames-per-second measurements.

VIII. ACKNOWLEDGMENT

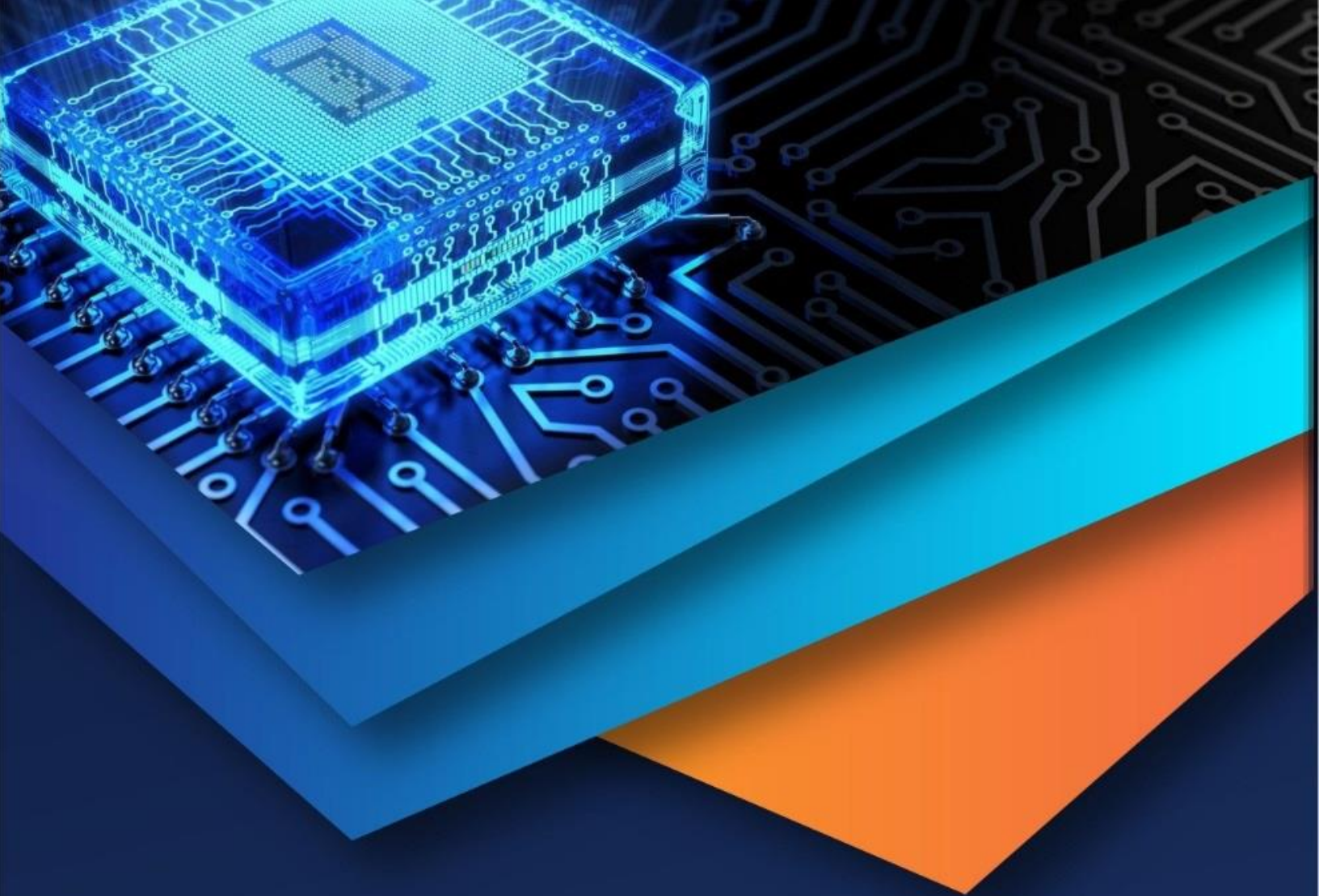
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