**Project Proposal**

**Automated Dashcam-Based Traffic Incident Detection**

### **1. Introduction**

Traffic accidents are a major cause of fatalities and economic losses worldwide. Existing traffic management systems primarily rely on fixed CCTV cameras, which have **limited coverage, particularly on highways and rural areas**. Additionally, many automated systems, such as Saher in Saudi Arabia, focus primarily on detecting **traffic violations** rather than accident classification.

This project proposes an **automated accident detection system** based on **dashcams** installed in vehicles. Unlike traditional systems, this approach leverages **mobile cameras** to provide **real-time, first-hand accident detection** with improved classification accuracy.

### **2. Objectives**

* Develop a real-time **accident detection system** using dashcam footage.
* Evaluate and benchmark **at least 10 different models** for object detection, accident severity classification, and motion analysis.
* Improve accident detection coverage beyond fixed CCTV cameras by leveraging dashcam mobility.
* Detect post-collision fires to assess further risks.

### **3. Methodology**

The proposed system consists of the following components:

#### **3.1 Dataset**

The system will utilize the **Nexar Collision Prediction Dataset** ([Kaggle](https://www.kaggle.com/competitions/nexar-collision-prediction/overview)), which consists of real-world dashcam footage collected from vehicles, annotated with accident occurrence labels. It includes video sequences leading up to collisions, metadata such as GPS coordinates, vehicle speed, and timestamps, allowing for the prediction of potential accidents before they occur. The dataset is particularly valuable for training and testing machine learning models aimed at accident detection and severity classification.

#### **3.2 Model Selection**

The following 10 models will be utilized:

##### **(1) Object Detection Models (Accident Detection from Video Frames)**

1. **YOLOv12** – Real-time object detection model optimized for speed and accuracy (**5\_CNNs**).
2. **Faster R-CNN** – High-accuracy object detection for detecting accidents in complex scenarios (**5\_CNNs**).
3. **SSD (Single Shot MultiBox Detector)** – Efficient object detection for real-time deployment (**3-2\_FeatureDERM**).
4. **DETR (DEtection TRansformer)** – Transformer-based model that improves detection robustness (**4-1\_NeuralNetworkFundamentals**).
5. **EfficientDet** – Optimized for efficiency and computational cost while maintaining high accuracy (**4-3\_NeuralNetworkTrainingAndEvaluation**).

##### **(2) Image Classification Models (Accident Severity Classification)**

1. **ResNet-50** – Deep residual network to classify accident severity from images (**5\_CNNs**).
2. **EfficientNet-B0** – Efficient and accurate classification model (**4-3\_NeuralNetworkTrainingAndEvaluation**).
3. **Vision Transformer (ViT)** – Transformer-based image classification model for severity assessment (**4-1\_NeuralNetworkFundamentals**).

##### **(3) Sequence-Based Models (Motion and Temporal Analysis of Accidents)**

1. **LSTM (Long Short-Term Memory Networks)** – Useful for processing sequential dashcam footage and predicting accident severity (**4-3\_NeuralNetworkTrainingAndEvaluation**).
2. **GRU (Gated Recurrent Units)** – More efficient than LSTM for analyzing motion data (**4-2\_NeuralNetworkLossFunctions**).

Each model will be evaluated using key performance metrics such as:

* **Accuracy, Precision, Recall, F1-score** (for classification models)
* **Inference time and computational efficiency** (for real-time applications)
* **Robustness against false positives and negatives**

### **4. Expected Outcomes**

* **Improved accident detection accuracy**, especially in highways and rural areas.
* **Enhanced severity classification** using a combination of CNNs and transformer-based architectures.
* **Reduced false positives and negatives** through a multi-modal detection approach combining motion analysis, object recognition, and fire detection.
* **Benchmarking results and insights** into why certain models perform better in specific scenarios.

### **5. Challenges and Considerations**

* **Data Privacy**: Encryption and anonymization techniques will be developed to protect driver and passenger identities.
* **Real-time Processing Constraints**: Model selection will focus on balancing accuracy and computational efficiency.
* **Dashcam Standardization**: Minimum hardware requirements for vehicles will be established to ensure uniform data quality.

### **6. Project Timeline and Action Plan**

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| --- | --- | --- | --- |
| Phase | Task | Start Date | End Date |
| Phase 1 | Research accident detection systems and dataset review | Mar 17 | Mar 23 |
| Phase 2 | Define methodology and system architecture | Mar 24 | Mar 30 |
| Phase 3 | Implement and train object detection/classification models | Mar 31 | Apr 5 |
| Phase 4 | Benchmark models, analyze results, and refine system | Apr 6 | Apr 12 |
| Phase 5 | Prepare final documentation and submit project | Apr 13 | Apr 20 |

**10 models**

### 1. Object Detection Models (Used for detecting accidents from dashcam footage)

1. **YOLOv7** – A fast object detection model, useful for real-time accident detection.
   * **Reference**: Convolutional Neural Networks (CNNs) – [5\_CNNs.pdf]​.
2. **Faster R-CNN** – High-accuracy object detection, useful for detailed accident analysis.
   * **Reference**: Convolutional Neural Networks (CNNs) – [5\_CNNs.pdf]​.
3. **SSD (Single Shot MultiBox Detector)** – A balance between speed and accuracy for accident detection.
   * **Reference**: Feature Detection & Representation – [3-2\_FeatureDERM.pdf]​.
4. **DETR (DEtection TRansformer)** – Transformer-based model that improves detection robustness.
   * **Reference**: Neural Network Fundamentals – [4-1\_NeuralNetworkFundamentals.pdf]​.
5. **EfficientDet** – Optimized for efficiency and computational cost while maintaining detection performance.
   * **Reference**: Neural Network Training & Evaluation – [4-3\_NeuralNetworkTrainingAndEvaluation.pdf]​.

### 2. Image Classification and Feature Extraction Models (Used for classifying accident severity)

1. **ResNet-50** – A deep residual network that can classify accident severity from images.
   * **Reference**: Convolutional Neural Networks (CNNs) – [5\_CNNs.pdf]​.
2. **EfficientNet-B0** – Efficient and accurate classification model.
   * **Reference**: Neural Network Training & Evaluation – [4-3\_NeuralNetworkTrainingAndEvaluation.pdf]​.
3. **Vision Transformer (ViT)** – A transformer-based image classification model for severity assessment.
   * **Reference**: Neural Network Fundamentals – [4-1\_NeuralNetworkFundamentals.pdf]​.

### 3. Sequence-Based Models for Motion Analysis (Used for analyzing accident motion patterns)

1. **LSTM (Long Short-Term Memory Networks)** – Useful for processing sequential dashcam footage and predicting accident severity.
   * **Reference**: Neural Network Training & Evaluation – [4-3\_NeuralNetworkTrainingAndEvaluation.pdf]​.
2. **GRU (Gated Recurrent Units)** – Similar to LSTM but more computationally efficient for analyzing motion data.

* **Reference**: Neural Network Loss Functions – [4-2\_NeuralNetworkLossFunctions.pdf]​.

### Best Model Selection for Your Project

If selecting **only a few models**, I recommend:

* **YOLOv7** (for real-time detection) or **Faster R-CNN** (for accuracy).
* **EfficientDet** (for optimized performance on limited resources).
* **ResNet-50** or **ViT** (for severity classification).
* **LSTM** (for motion sequence analysis), with **GRU** as a more efficient alternative.