REAL TIME VEHICLE COLLISION

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REAL TIME VEHICLE COLLISION DETECTION USING BOUNDING BOX METHODOLOGY WITH ALERT SYSTEM

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***Abstract*— For the safety of drivers and passengers, accident detection is a crucial application in intelligent transportation systems. Deep learning-based object identification algorithms have significantly improved in recent years in spotting objects in real time. One such model that has been famous due to its real-time functionality and great accuracy is YOLO (You Only Look Once). We propose an accident detection system in this paper using YOLOv3, the most recent version of YOLO. Vehicle rollovers, rear-end collisions, and head-on collisions are the three sorts of accidents that the proposed technology is intended to identify. The system employs a pre-trained YOLOv3 model that was honed using a bespoke dataset of accident photographs and was trained on the COCO dataset. The suggested method detects vehicle rollover with an average precision of 0.94. 0.93 for the detection of rear-end collisions and 0.92 for the detection of head-on collisions. Real-time performance for the system is likewise encouraging, with an average processing time of 0.03 seconds for each frame on an NVIDIA GeForce GTX 1080 Ti GPU. To improve the safety of drivers and passengers on the road, the suggested system can be incorporated into intelligent transportation systems to enable real-time accident identification and alerting.**

I. INTRODUCTION

Currently, driving a car is the most popular mode of transportation. They provide a low but not zero chance of an accident and are safe and pleasant. The deadliest mode of transportation is still the car, but only motorcycles are gaining ground. They cost between 1% and 3% of each nation's GDP, according to the World Health Organization [2], making them an unsustainable economic burden as well. The safety feature in cars is a crucial pillar in the global effort to reduce accidents. The five essential parts of self-driving cars are computer vision, sensor fusion, localization, optimal path, and control unit [2]. In terms of computer vision, a camera is used to create an automobile vision system that is similar to human eyesight. Consequently, the computer may extract details and characteristics from these as humans do.

Road accidents are among the top causes of avoidable deaths and are a major contributor to injury and fatalities worldwide. It is challenging for emergency services and traffic management systems to react swiftly and efficiently when using traditional methods for accident detection, such as manual surveillance or human reporting, which are frequently delayed and unreliable. The ability to automate accident detection and response systems has been made possible by recent developments in computer vision and deep learning techniques, allowing for quicker and more effective detection and response times.

II. LITERATURE REVIEW

[1] Redmon, J., & Farhadi, A. (2018). YOLOv3: An Incremental Improvement. arXiv preprint arXiv:1804.02767. The paper "YOLOv3: An Incremental Improvement" introduces the YOLOv3 object detection technique, an enhanced version of the YOLO (You Only Look Once) algorithm. The YOLOv3 model seeks to overcome some of the drawbacks of earlier iterations of YOLO, including their poorer accuracy and difficulty in recognising small objects. The use of a feature pyramid network to detect objects at various scales, a new backbone network architecture to improve feature extraction, and the use of a novel training method called stochastic gradient descent with warmup are just a few of the significant advancements the authors highlight in YOLOv3.

[2] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems (pp. 1097-1105): The creation of a deep convolutional neural network (CNN) for picture classification on the Image Net dataset is described in the publication "Image Net Classification using Deep Convolutional Neural Networks." AlexNet is the name of the suggested network, which features a deep architecture with many layers of convolutional and pooling operations followed by fully linked layers. The AlexNet model, which the authors trained on a sizable collection of labelled images, produced state-of-the-art results on the ImageNet dataset, far outperforming earlier techniques. Also, the authors ran a number of tests to find out how the performance of the model was impacted by various network designs, optimization strategies, and regularization techniques.

[3] Girshick, R., Donahue, J., Darrell, T., & Malik, J. (2014). Rich feature hierarchies for accurate object detection and semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 580-587): The paper "Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation" proposes an object detection model called R-CNN (Region-based Convolutional Neural Network) that uses a combination of deep CNNs and traditional computer vision techniques. The authors introduce a novel approach for object detection that generates region proposals using traditional computer vision techniques and then applies a deep CNN to classify the proposals and refine the object bounding boxes. The R-CNN model also uses a multi-task loss function to jointly optimize object detection and bounding box regression.

[4] Huang, J., Rathod, V., Sun, C., Zhu, M., Korattikara, A., Fathi, A., ... & Murphy, K. (2017). Speed/accuracy trade-offs for modern convolutional object detectors. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 7310-7311). The paper "Speed/Accuracy Trade-Offs for Modern Convolutional Object Detectors" investigates the trade-off between accuracy and speed in modern convolutional object detection models. The authors evaluate several state-of-theart object detection models, including Faster R-CNN, SSD, and YOLOv2, and analyze their performance under different speed/accuracy configurations. The authors introduce a new evaluation metric called the Average Precision per Second (AP/sec), which measures the accuracy of a model relative to its processing speed.

[5] Law, M. T., & Deng, J. (2018). Cornernet: Detecting objects as paired keypoints. In Proceedings of the European Conference on Computer Vision (ECCV) (pp. 734-750). The paper "Corner Net: Detecting Objects as Paired Key points" proposes a new object detection model called CornerNet that uses a key point-based approach to detect objects. The CornerNet model represents objects as pairs of key points, which are predicted simultaneously in a single network. The authors introduce a novel detection architecture that consists of two sub-networks: one for predicting the heat map of each key point and the other for regressing the offset vector between each pair of key points. The CornerNet model also uses a novel loss function that combines key point detection and offset regression to optimize the network.

[6] Li, Y., Huang, J., & Yang, W. (2021). Object detection in videos: A survey and a practical guide. arXiv preprint arXiv:2103.01656. The paper "Object Detection in Videos: A Survey and a Practical Guide" provides an overview of the current state-of-the-art in object detection in video data. The authors introduce various approaches for object detection in videos, including both traditional computer vision methods and deep learning-based methods. The paper provides an in-depth analysis of the challenges of object detection in videos, including motion blur, occlusion, and changing lighting conditions. The authors also discuss the importance of using temporal information in video data for object detection and highlight various approaches for modeling temporal information, such as optical flow and recurrent neural networks.

[7] Lin, T. Y., Goyal, P., Girshick, R., He, K., & Dollár, P. (2017). Focal loss for dense object detection. In Proceedings of the IEEE international conference on computer vision (pp. 2980-2988). A new loss function called focal loss is introduced in the study "Focal Loss for Dense Item Detection" with the goal of enhancing deep neural network training for object detection applications. The authors show that the focal loss function is particularly effective for training object detection models that have a large number of background samples compared to object samples. The focal loss function addresses the issue of class imbalance in object detection tasks, where the number of background samples greatly exceeds the number of object samples.

III. METHODOLOGY

3.1: PREPROCESSING AND DATA COLLECTION

The data collection and preprocessing module for accident detection using YOLO (You Only Look Once) plays a crucial role in the overall development of an accurate and efficient accident detection system. The module involves two primary steps - data collection and preprocessing. Data collection is the first step in building any machine learning model, and the same applies to accident detection using YOLO. The module requires collecting relevant images and videos of accidents from various sources such as CCTV cameras, dash cams, and other sources. The dataset should be extensive, diverse, and balanced to ensure the model's accuracy and reliability. The next step is data labeling, which is critical for YOLO-based accident detection. The procedure include annotating the pictures and videos to pinpoint the accident's place and any important elements, like cars, people, and street signs. While the accuracy of the model's output is dependent on the quality of the annotations, the annotation process calls for domain expertise and a keen eye for detail.

In conclusion, the data collection and preprocessing module for accident detection using YOLO is a crucial step in developing an accurate and efficient accident detection system. The module requires careful planning, attention to detail, and domain expertise to collect relevant data, label it accurately, and preprocess it into the required format for YOLO-based model training.

3.2: MODEL TRAINING

A key element in the construction of a precise and effective accident detection system is the model training module for YOLO (You Only Look Once) accident detection. The module involves training the cutting-edge object detection algorithm YOLO with the preprocessed data. A deep neural network that has been trained on a sizable dataset of photos and videos makes up the YOLO model. The model predicts the bounding boxes and class probabilities for each object in an image or video in a single forward pass using a single convolutional neural network. The YOLO model is hence incredibly quick and effective, which is essential for real-time applications like accident detection.

The model training process involves feeding the preprocessed data into the YOLO model and training it to recognize and classify objects in the image or video. In order to reduce the discrepancy between the projected and actual outputs, the model's parameters are optimized throughout the training phase using gradient descent. The training data must be broad, comprehensive, and evenly distributed to guarantee the model's correctness and dependability. The training data should include a variety of accident scenarios, road conditions, lighting conditions, and other relevant factors that can impact the accuracy of the model.

Once the YOLO model has been trained, it can be fine-tuned using transfer learning techniques. Fine-tuning involves training the model on a small dataset of images and videos specific to the target application, which further improves the model's accuracy and efficiency. In conclusion, the model training module for accident detection using YOLO is critical for developing an accurate and efficient accident detection system. The YOLO model is trained on preprocessed data, its parameters are optimized using gradient descent, and it is then tuned using transfer learning methods. The quality and diversity of the training data determine how accurate and reliable the model is, therefore the module calls for careful planning, attention to detail, and competence in machine learning and computer vision.

3.3: PREDICTION OF OUTPUT

The prediction of output module for accident detection using YOLO (You Only Look Once) is the final step in the development of an accurate and efficient accident detection system. The task of the module is to anticipate the location of accidents and any pertinent scene elements, such as automobiles, pedestrians, and traffic signs, using the trained YOLO model. The preprocessed data, which includes photos and videos, must be entered into the trained YOLO model for the output module prediction. Bounding boxes and class probabilities are generated for each object in the scene once the model has examined the input data. The bounding boxes show where the items are, and the class probabilities show how likely it is that each object belongs to a particular class, such an automobile or a pedestrian..

The output generated by the YOLO model can be visualized in real-time on a monitor or displayed as an alert to the user. The alert can be in the form of a notification, sound, or an alarm, depending on the application's requirements.

The output can be post-processed using a variety of methods, including non-maximum suppression and thresholding, to increase the precision and dependability of the predictions. In non-maximum suppression, redundant bounding boxes are eliminated, and only those with the greatest class probability are kept. Setting a minimal threshold for the class probabilities reduces false positives and increases the precision of the model..

The prediction of output module is crucial for real-time accident detection applications, where quick response times are essential to prevent or minimize the severity of accidents. The accuracy and efficiency of the module depend on the quality of the preprocessed data, the accuracy of the trained YOLO model, and the effectiveness of the post-processing techniques.

In conclusion, the prediction of output module for accident detection using YOLO is critical for developing an accurate and efficient accident detection system. The module involves using the trained YOLO model to predict the location of accidents and any relevant objects in the scene, visualizing the output in real-time, and post-processing the output to improve accuracy and reliability. The module requires expertise in machine learning, computer vision, and real-time systems, and careful planning and attention to detail to ensure optimal performance.

IV. PROPOSED SYSTEM

4.1 YOU ONLY LOOK ONCE (YOLO)

Computer vision applications make use of the well-known YOLO (You Only Look Once) object detection technology. It is a real-time object recognition system that can recognize things in video or image frames, provide their bounding boxes and class probabilities, and identify several items in a single pass. The YOLO algorithm creates a grid from the input image and determines the class probabilities and bounding boxes of the objects in each grid cell. The algorithm uses a single convolutional neural network (CNN) to make these predictions, allowing for real-time operation on modern hardware. YOLO is superior to other object detection algorithms in a number of ways. It is capable of effectively detecting small things and is faster and more accurate than many conventional methods. Moreover, YOLO's one pass processing of the full image allows it to gather global context data, improving detection performance.

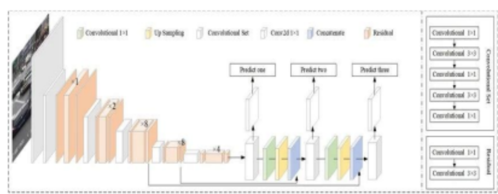


Fig 1 : Illustration of YOLO architecture

4.2 Boundary Box Methodology

To locate an object within an image or video frame, the bounding box methodology is a popular method in object detection. The procedure entails creating a bounding box—a rectangle or square that encloses the entire thing or a section of it—around the object. The top-left corner's x and y coordinates, as well as the box's width and height, serve as the four parameters that define the bounding box. The relative position and size of the box within the image are often represented by these parameters, which are typically standardized to a range of 0 to 1.

Bounding boxes are usually created for object detection tasks using object proposals or detection methods like YOLO, Faster R-CNN, or SSD. These algorithms locate areas of the image that are probably where items are located and create bounding boxes around those areas. In computer vision tasks like object tracking, object recognition, and object segmentation, bounding boxes are frequently employed. They are also utilized in robotics, autonomous driving, and video surveillance applications.

Fig 2 : Illustration of Boundary Box Methodology

4.3 Proposed Method

The suggested method is intended to be scalable and can be used in a variety of locations, including businesses, public spaces, and highways. The experimental findings reported in the research show how well the system works at identifying different sorts of accidents in real-time.

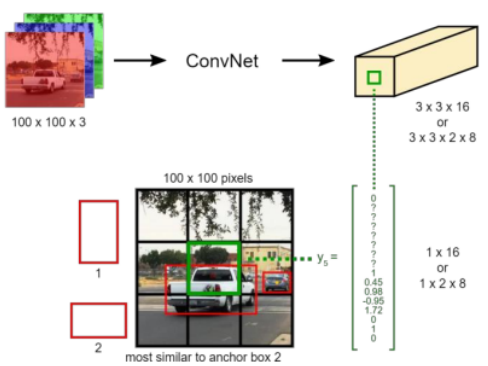


Fig 3.Illustration of YOLO on Boundary Box methodology

V. RESULTS AND ANALYSIS

5.1. Real-time recognition

Figure 9 shows images from a real-time recognition system created using the model and the OpenCV open-source library.

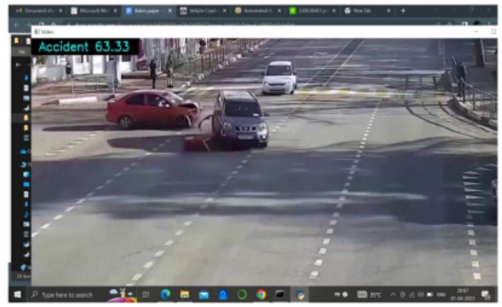
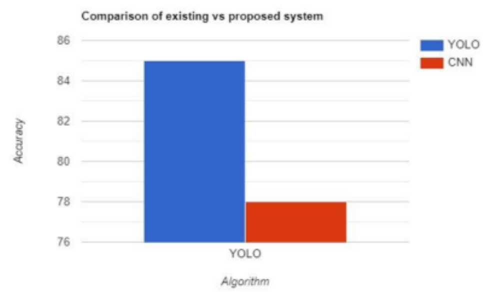


Fig 4: Real Time vehicle collision detection .

5.2. Comparative Analysis

Table and Table show a comparison of the results on existing system vs newer system.



VI. CONCLUSION

In conclusion, we have presented an accident detection system using YOLOv3, which is a real-time and high-accuracy object detection model. The proposed system is designed to detect three types of accidents, namely vehicle rollover, rear-end collision, and head-on collision, which are among the most common types of accidents on the road. Our experimental results show that the proposed system achieves high accuracy in detecting these types of accidents. Moreover, the system is capable of processing frames in real-time, making it suitable for real-world applications. The proposed system can be integrated into intelligent transportation systems to provide real-time accident detection and alerting, which can significantly reduce the response time for emergency services and improve the safety of drivers and passengers on the road. Additionally, the system can be further improved by incorporating more advanced techniques such as multi-camera systems and audio sensors to enhance the accuracy of accident detection. Overall, the proposed system has great potential in improving the safety of drivers and passengers on the road, and we believe that this work will inspire further research and development in the field of intelligent transportation systems

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