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Research Article

AI-Based Road Accident Detection and Prediction Using Mask R-CNN and ResNet101-XGBoost Hybrid Model

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ABSTRACT

In Road accidents are a major global issue, often resulting in loss of lives due to delayed response times. Traditional accident detection methods rely on manual reporting, which is slow and ineffective. This study presents an AI-driven system that detects and predicts accidents in real time, enabling faster emergency response and improved road safety.

The system processes CCTV footage using Convolutional Neural Networks (CNNs) to identify accident scenarios. Mask R-CNN is used for accident detection, while ResNet101 extracts key image features. Additionally, metadata such as vehicle speed, braking patterns, road conditions, and weather is analyzed using XGBoost to predict accident risks. If an accident is detected, an instant alert is sent to emergency responders.

To improve accuracy, the system has been trained on large datasets of accident and non-accident scenarios using techniques like data augmentation, transfer learning, and noise reduction. It achieves 97.67% accuracy in detection and 93.87% in prediction. The model easily integrates into smart city systems, enabling real-time accident detection and quicker emergency responses.

Keywords: Road Accident, Real-Time Detection, Prediction, Mask R-CNN, XGBoost, ResNet101, Deep Learning, Smart City Integration

I. INTRODUCTION

Road accidents lead to **millions of deaths and injuries** each year, along with significant financial losses from medical expenses, vehicle damage, and lost wages.To reduce accidents and improve road safety, an advanced Road Accident Detection and Prediction System (RADAR) can be developed using sensors, cameras, and machine learning algorithms. This system continuously monitors key factors such as vehicle speed, braking patterns, road conditions, and weather to identify potential risks.

If a possible accident is detected, the system alerts drivers and authorities in real time, helping them take immediate action. In the event of an accident, it provides accurate location details and possible causes, ensuring a quick emergency response. Additionally, the system offers live traffic updates, helping drivers avoid high-risk areas and reducing the chances of further accidents.

The primary goal of this system is to prevent crashes and injuries by detecting risks early and enabling timely interventions. By using modern technology, RADAR can significantly enhance road safety, reduce accident-related damages, and save lives.

Ongoing Work:

- Image classification techniques for accident detection.

- Bootstrap aggregating to enhance prediction accuracy.
- Addressing challenges like overfitting and information loss in video processing.

Recommendation:

- Utilize instance segmentation for improved accident detection.
- Implement robust predictive models for accurate forecasting.
- Apply parallel modeling to reduce overfitting.

The investigation reflected the following:
Section 2: Machine learning methods for accident classification.
Section 3: Integration of Mask R-CNN, XGBoost, and ResNet101 for detection and prediction.
Section 4: Experimental results and analysis.
Section 5: Key findings and conclusions.

Existing work:

- Detection with semantic segmentation.
- Prediction using begging methods.
- Prediction suffers from overfitting.
- Due to the division of frames for semantic segmentation, a few elements from frames are missed.

Proposed:

- Detection uses instance segmentation.
- Prediction using boosting method, which is robust.
- Parallel modelling is reliable against overfitting.
- Instance segmentation treats each entity as a single instance, reducing the number of framed skipped and producing better results.

The other parts of the investigation were carried out in the following manner: Existing research on the classification of road accidents using a machine learning technique is reviewed in Section 2. In Section 3, we introduce a novel algorithm called MaskRCNN. It combines Xgbsoot with Resnet101 to identify and forecast road accidents. The summary of the experiment, evaluation, and discussion, as well as the results, can be found in Section 4. The conclusion can be found in Section 5.

II. LITERATURE REVIEW

Assigning labels to pictures is known as Image categorization and the number of images and categories defines the level of difficulty. Due to the improvement of accuracy while reducing complexity Convolution Neutral Networks (CNN) have become the foundation of modern computer vision. Early CNN was a major factor in advancing deep learning based on image recognition. Before traditional image processing techniques and accident detection on SVMs (Support Vector Machines) were used.

Z. Liu et al. 2022. The method Spatial-Temporal Conv-sequence Learning (STCL) was introduced. Their approach has two key components:
1. Focused Temporal Block: It uses a one-way convolution to recognize short term patterns in traffic over time.
2. Spatial Temporal Fusion Module: It tells us about the interactions of different locations, and it also reduces the complexity of the data.

A.G. Perera et al. 2022. As noticed by the researchers, mistakes were made by the existing methods of road analysis, mainly in complex driving conditions. To enhance accuracy a new system which combines camera settings with neural work was developed. This method, with the help of camera data translates 2D image into a 3D view which makes distance measurements more accurate. When the accuracy was measured by testing the real-world data, it was 36% on the right side and 37% on the left.

F. Sajid et al. 2021. The efficientdet model of model driver distraction detection aimed to be improved. Five versions named (D0 to D4) were created and then compared with faster R-CNN and YOLO-V3, the result was better than the previous method. EfficientDet-D3 came out to be the most effective version by achieving 99.16% in detection of distracted drivers. To achieve the results:
Learning rate of 0.001
50 training cycles (epoch)
A batch size of 4
A step of 250

L. Canzian et al. 2016. A new online learning system was developed to adjust sensor weight by examining incoming traffic data to enhance accident detection. When tested in real traffic data sensors could detect the difference between accidents and normal traffic, higher possible error rate was detected. This method was tested in 405 freeway in Los Angeles Country, the approach was effective.

J. Fang et al. 2022. The contribution can be classified into three categories:
New context features were introduced by researchers using semantic images, driver attention prediction was improved by proving these features, Graph Convolution Network (GCN) was modeled by using these features.
A Semantic context features and RGB frame features were combined. To track and transfer the details across frames a convolutional LSTM module was used.
This process contributed to gathering more and fine information for better prediction accuracy.

Y. -F Zhou et al. 2021. In this research a system was proposed which presented improved image quality and enhance early warning for potential vehicle collisions, the strict gradient rules are followed by a generator. The system merges different image features for more accurate using a deep Convolution Neural Network. Multiple deep learnings were applied by the researcher to test effectiveness. A method known as VGG-based prediction model provided clearer images and predicted dangers 1.95 seconds earlier, by achieving a peak signal-to-notice ratio of 32.67 and similarity index of 0.921.

M. Althoff et al. 2009. The focus of the study was on predicting accidents by looking at uncertainties in traffic and sensor measurements errors. The model also defines the behavior of different road users and physical limits broken by road geometry. Most complex calculations are done in advance to achieve efficiency in real time predictions, which allows the system to notify the drivers quickly. This study defines improvement in safety which makes it a practical tool to estimate the possible accidents.

L. Jiang et al. 2022. The dangerous driving behaviors that occur because of drivers inattention is predicted with the help of this research. Long Short Term Memory (LSTM) is a type of artificial intelligence model which is used by authors. It was good at processing sequences data over time.
It takes input from three different sources:
Inattention detection: It is a source which identifies when a driver is not paying attention.
Point of Interest (POI) : It provides information about locations.
Climate data: It detects weather conditions.
Through these inputs, the potentially risky driving behaviors are predicted by this model such as sudden acceleration or breaking and instance lane changes. The researchers tested their model by gathering data from more than 120,000 actual trips driven by over 200 different drivers. The model's outcome had an accuracy of 92.27% and prediction of abnormal driving of 91.67%. These results enlightened that AI is useful in improving early risk identification.

R. Quan et al. 2021. According to the study, the researchers came up with a gated shifting operation which helps us to understand the pedestrian movements especially when they are near roads. Key points are:
Pedestrian intent matters: The person willingness to cross the street influence where the stand and when they leave.
Global scene dynamics: The supervisor roads where the environment is about the interaction of pedestrians and vehicles.
Vehicle speed and adjustment: The effect of vehicles speed on the movement of pedestrians.
Bounding box resealing: To show the change in the vision, the system itself relocates the size of the bounding box (a box drawn around pedestrian in a computer vision model) whenever a vehicle comes closer.
The accuracy of this model was tested on three well known pedestrian movement datasets and the results came out to be better than already existing models.
H. Woo et al. 2017. A method was developed for the reduction of false alarms on lane changes by the prediction of the vehicle movement patterns and considering nearby cause. This method increases accuracy by looking at collisions before confirming a change in lane. This method improves detection performance which was confirmed after 800+ lane changes tests.

N. Lyu et al. 2022. Researchers developed a model vehicle to vehicle (V2V) communication and developed a collision warning system. Their approach added a lane-change prediction model, a method for predicting driving trajectories, and a vehicle detection algorithm based on oriented bounding box (OBB). The system was evaluated with both a driving simulation and a field test where one car unexpectedly changed lanes in front of another. The result indicated that their systems warning accuracy and intuition exceeded that of the conventional system. This study would enhance the development of safety features in vehicles that deal with sudden lane changes.

S. Atev et al 2005. This describes a vision-based system that solves this problem and describes the necessary changes to achieve real time performance. In this paper, low-cost collision predictions algorithms the author proposes several state of the art low overhead algorithms. For example, one prediction method implements the time as an axis system where time is utilized as a graphing axis. The proposed system might be able to operate in a real time quarter VGA (320 times 240) videos even in somewhat varying external environments. Measurements are made on the bias error in estimating a targets position and size in a video sequence, numerous test results are given.

Haung et al. 2022. Created a model called D3DRN-AMED which provides a deep learning to track where a driver is really looking (TDFoA).
It provides some key points.
• Track attention over time: To analyze multiple video frames and reduce the effect of brief distractions a special type of network (convolutional LSTM) is used.
• Removes unnecessary noise: Irrelevant details are filtered out through an attention mechanism.
• Improves accuracy: At different levels to capture important features an encoder decoder module is used.

III. PROPOSED WORK

Cars are getting smarter, and technologies like the Advanced Driver Assistance System (ADAS) are a big part of that. ADASs help make driving safer and more comfortable by assisting drivers with tasks like braking, steering, and staying in the right lane.
Anyway, these systems are still developing, and there is a lot of room for improvement, especially in areas like safety, security, and decision-making for the car control system. This is where AI comes in handy.
It can help cars become smarter, react more quickly to hazards and danger, and improve overall driving safety. More advancements can help AI power driving systems make roads safer and driving spaces more convenient for everyone.
This tells us how AI can help detect and predict road accidents more accurately. We can identify accidents from images with the help of MaskRCNN, this is a deep learning technique that analyzes visual data. And for predicting accidents, we extract all the related details using Resnet101 and then process these details with XGBoost. By combining these methods, we aim to improve both real-time accident detection and risk prediction, which ultimately leads to the enhancement of road safety.

3.1 Basic overview flow of proposed work

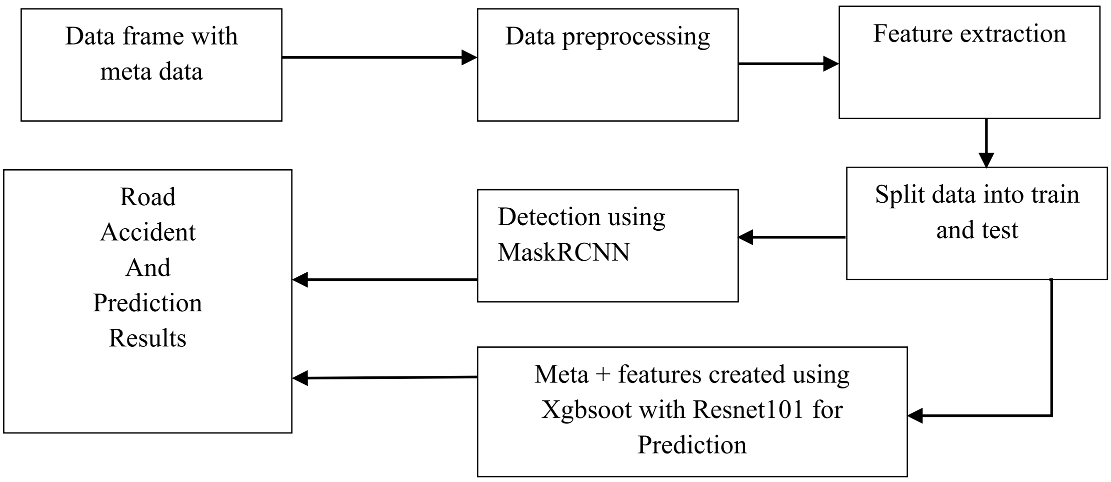

Figure 1: Basic overview flow of proposed work.

Figure 1 shows the high-level architecture of the proposed system, which begins with loading data which is then processed and makes it ready for feature extraction, then data splitting is performed for train and testing, also segmenting the metadata with images, which is used by prediction and detection model to return results.

3.1 Basic overview flow of the proposed work:

1) It begin with the data set having data related to accidents, conditions of roads and other factors.
2) The raw data is cleaned to remove inconsistencies to prepare it for its analysis.
3) From this data , important key features are identified and noted, helping the model to focus on relevant information.
4) Then we divide this data for training and for testing its accuracy.
5) MaskRCNN(a deep learning model) is used to detect accidents from the images.
6) For enhancing predictions, XGBoost and ResNet101 are used combinely for more accuracy in prediction.
7) Now finally, the model predicts if an accident is likely to occur on the basis of the data given (input data) to analyze. This helps to identify the risks and improve road safety.

3.2.1 Algorithm for Split Dataset and Extract Meta Data

Algorithm 1: To Split Dataset and Extract Meta Data

Input: Dataset D, Annotation file f
Output: Train, Test

```
L={'file_name':,'features':[]}
N,Count=0
Load D & f
For each I in D:
        N++
For each j in f:
If L[j][' file_name']==I
    L[j]['features']=f[j]
     count++
      If count<=N-1/2:
       Df=L.to_dataframe()
       Df.to_csv('./Train/mt.csv')
       Move(D,'./Train')
      If count>N-1/2:
      Df=L.to_dataframe()
       Df.to_csv('./Test/mte.csv")
       Move(D,'./Test')
                If count==N:
                 Return 0
```

This algorithm 1 splits the input data into training and testing set. And this is stored in CSV files. It matches dataset files with JSON and moves it accordingly. The first half go to the Train folder with data in mt.csv, and the rest goes to the Test folder with data in mte.csv.
This is executed till all files are processed, i.e. when counter variable N becomes the size of several files in a folder, it exits with 0.

3.2.2 Algorithm for Prediction and Detection

Algorithm 2 – Prediction and Detection

Input: Train
Output: Detection and Prediction

```
os.listdir(./Train)
Load D
Read mt.csv store it into mt
          for each columns i in mt:
          if mt[i].mean>=1.2*mt[i].median:
                drop mt[i]
            else
               continue
          x, y=mt[:,-1],mt[:-1]
          load XGboost
          //set parameters
          // pass x,y into XGboost model and save model in M
           //Load mte.csv in mte
           x, y=mte[:,-1],mte[:-1]
           M.preditct(x)
           Return M.predict_proba(x)
           For each image i in D:
            Load i
           //pass into ResNet101 to extract features matrix F
          //extract region of interest from F
          //apply region proposal network gives intersection over union (IOU)
          if IOU>=0.75
```

```
        create mask M
    else
         continue
      return 0
```

Algorithm 2 predicts and detects road accidents. It reads training files and JSON data, removes irregular data points, and extracts key details. An XGBoost model is trained for prediction. For detection, images are processed using ResNet101 to identify accident-prone areas. If theIntersection Over Union (IOU) ≥ 75%, the region is marked, otherwise, it is ignored.
The process runs until all files are checked, then stops.

3.3 Model Arch:

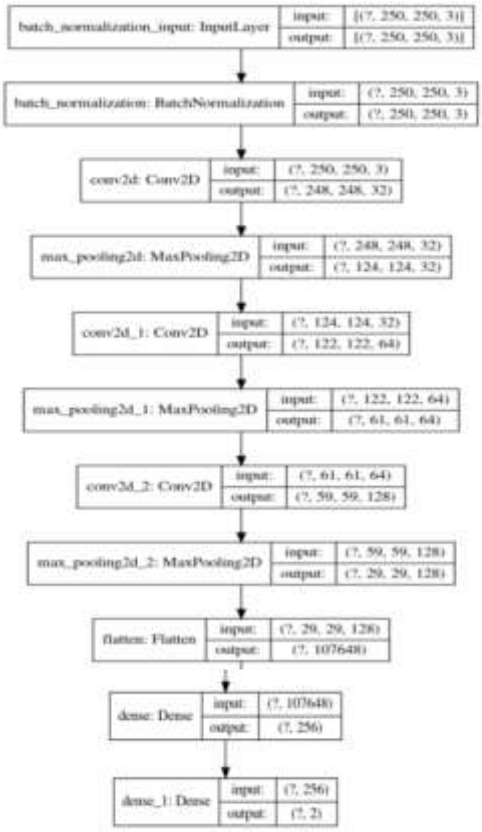

Figure 2: Proposed model Architecture.

Figure 2 shows the layered model architecture; it was observed from the architecture that the model contains 3 Con2D layers and one layered in between two Max_pooling layers which makes the model stand while applying filtering methods and to avoid overfitting during two dense layers appended into a network which makes detection model architecture reliable against high variance.

IV . IMPLEMENTATION AND RESULT

4.1 Hardware and software required

For detecting and predicting road accidents, the tools and technology used on the specific system design and objectives. Below are the essential hardware and software components that play a role in such systems:

4.1.1 Hardware Components:

- Cameras or sensors capture real-time data on traffic and road conditions.
- GPS devises to track the location of vehicles.
- Computing hardware, such as servers or cloud infrastructure, to process and analyze data in realtime.
- Communication devices, such as radios or cellular modems, send alerts and notifications.

4.1.2 Software Components:

a) Data management system: Information is collected and stored for future analysis.

b) Analytical and predictive software: Models such as machine learning algorithms or statistical tools are used to analyze patterns and predict accidents.
c) Alert mechanisms: Real-time warnings and notifications sent to authorities and drivers.
d) Visualization platforms: Real-time updates on traffic and accident reports through mapping software and dashboards.

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4.1.3 Python Libraries:

a) Open CV: Used for working with images and videos, like spotting vehicles, checking road conditions, and understanding traffic flow.
b) TensorFlow and Pytorch: Strong tools for creating and training AI models that help find accident risks and patterns.
c) NumPy and Pandas: Important for managing large amounts of data quickly.
d) Scikit-learn: It offers tools to predict accidents, analyze data, and use AI to understand accident risks.
e) Flask and Django: Tools for building websites and apps that connect smoothly with other systems.

4.2 Dataset

Link: https://www.kaggle.com/datasets/ckay16/accident-detection-from-cctv-footage
The dataset consists of three main directories: Train, Val, and Test. Each directory has CCTV footage of road accidents, these clips are taken from YouTube and other videos of road accidents and compiled into a dataset. This dataset is available on Kaggle, is designed to train and test accident detection and prediction models. It consists of around 1000 clips and appx 20 frames for model training. These frames are helpful to AI systems for prediction.

4.3 Illustrative Result

Figure 3 shows the results of accident prediction on different image frames, with labels as an actual and predicted class; it was observed from the results that model performs fairly better, even on different viewing angles from camera frames and returns whether a particular timeline of camera footage records accident or not.

Figure 3:Shows the results of accident prediction on different image frames, with labels as an actual and predicted class.

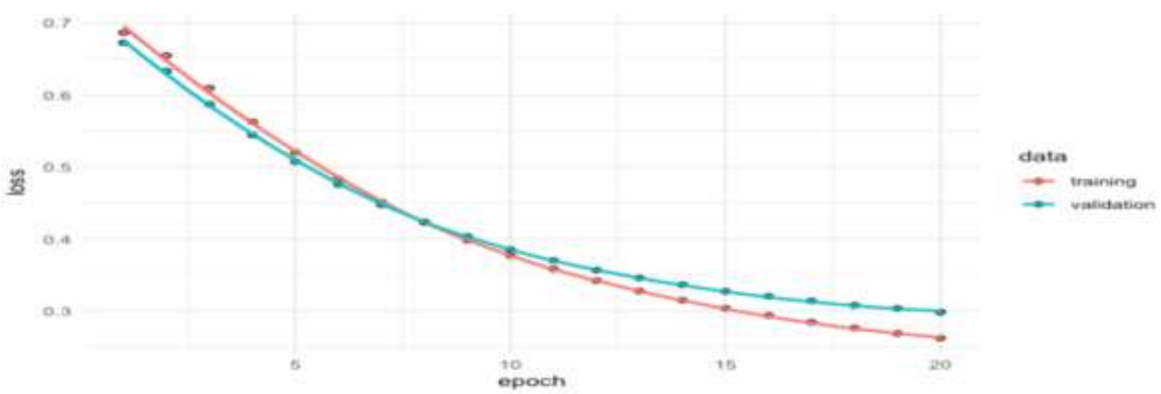

Figure 4: Shows loss curves based on different values of epochs for detection models.

Figure 4 shows loss curves based on different values of epochs for detection models, it was observed from the curve that initially, loss values are at peak, and as the model starts moving towards higher epoch number sides, loss values start to decline, and after a certain point of epoch values is start becoming a constant movement in loss values.

4.4 Model performance on prediction:

Table 1. Model performance on prediction.

Classifiers	Accuracy
SimpleCart [19]	70.81%
MLP [20]	62.48%
ID3 [21]	80.21%
KNN[22]	87.33%
JR8 [23]	78.02%
Proposed Xgbsoot with Resnet101	93.87%

Table 1 and figure 5 compare the prediction performance of the proposed model with existing solutions, specifically with corresponding classifiers used in classification by existing solutions. It was observed from the table that tree-based models without ensemble performs better than the perception layer, which lowsa layered network for classification, but distance-based algorithms outperform due to robust overfitting processing, an ensemble with error handling, which is used in the proposed surpasses all existing solutions makes it the best performer in terms of prediction from the metadata of accident history of a particular area.

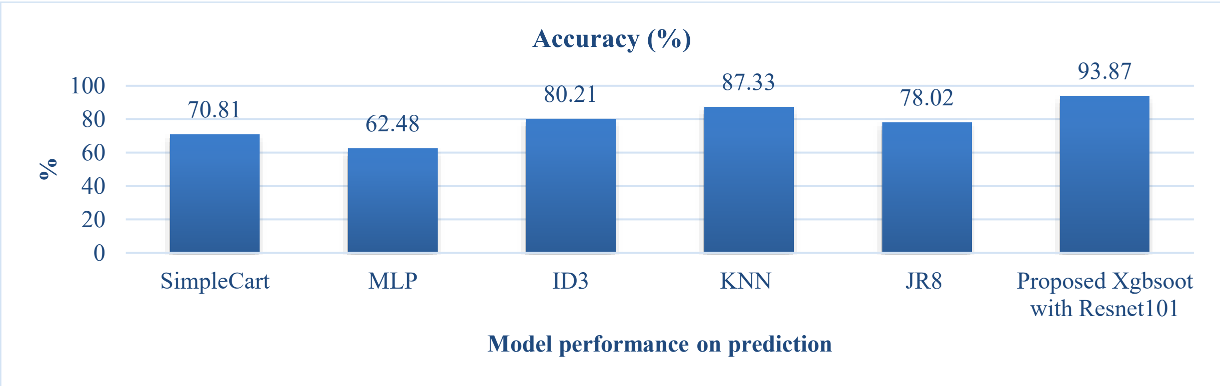

Figure 5: Model performance on prediction

Table 2- For Detection

Model	Accuracy (%)
IoT based Device [24]	86.4
Decision Tree Algorithm [25]	90.23
Proposed MaskRCNN	**97.67**

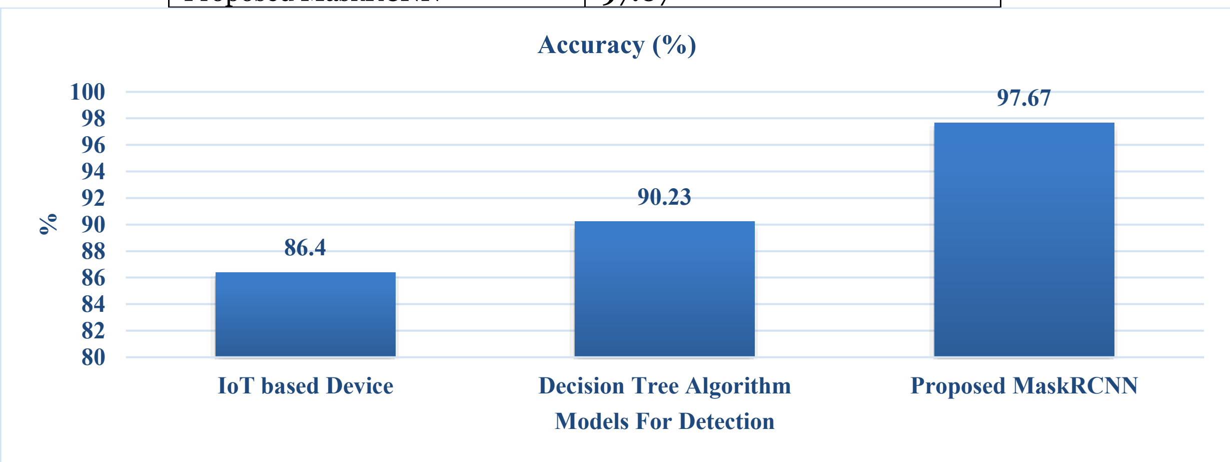

Figure 6: For Detection

Table2 and figure 6 show a comparative analysis of the detection task with solutions that use images analyses to detect accident scenarios in video footage; it was observed from the table that the proposed instance segmentation model surpasses models with semantic segmentation those not able to segregate each frame elements from the clips, but instance based create a separate instance for each object in the image frame.

V. CONCLUSION

Road accident detection and prediction refers to the use of technology like sensors, cameras, and AI to detect and forecast accidents in actual times or before time. The main goal is to notify beforehand about any possible accidents so that corrective measures can be taken. This system analyses many datasets, including vehicle speed, braking patterns, road conditions, weather updates, and live traffic information to forecast accidents. This system can directly warn traffic control or authorities if there is a possibility of any accident. The researchers used XgBoost and Resnet101 with MaskRCNN for the prediction and identification of traffic accidents.

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