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Helmet Detection and Number Plate Detection

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ABSTRACT

Helmet detection and number plate detection are two important tasks in the field of computer vision with various applications in the areas of road safety, law enforcement, and intelligent transportation systems. Helmet detection involves detecting the presence or absence of helmets worn by motorcyclists, which can help prevent accidents and reduce the risk of head injuries. On the other hand, number plate detection involves recognizing and localizing the license plates of vehicles, which is essential for identifying and tracking vehicles for various purposes, such as toll collection and traffic law enforcement. Deep learning methods have demonstrated encouraging outcomes in tasks involving the detection of helmets and number plates. However, the accuracy and robustness of these methods still need to be improved to address real-world challenges such as varying lighting conditions, occlusions, and complex backgrounds. This abstract provides an overview of the importance of helmet detection and number plate detection, and highlights the potential of deep learning-based approaches for solving these tasks.

Keywords- Helmet Detection, Number plate detection, vehicle identification, deep learning, YOLO algorithm

1. INTRODUCTION

Motorcycle accidents have become a major concern in recent years, with the number of accidents increasing at an alarming rate. Motorcycle accidents account for a significant proportion of road traffic deaths and injuries worldwide. According to WHO road traffic dead involving two and three wheelers are 43% of total road death. [1] In many cases, Head injuries stand as the predominant cause of fatalities and severe injuries in motorcycle accidents. The reasons for the increase in motorcycle accidents are multifaceted and can be attributed to various factors, such as inadequate road infrastructure, lack of proper training and education, and non-compliance with safety regulations. In addition, the increase in motorcycle usage as a means of transportation, especially in densely populated urban areas, has also contributed to the rise in accidents. To address this issue, it is essential to implement effective measures to ensure road safety for motorcyclists. One such measure is the use of helmet detection technology, which can detect whether motorcyclists are wearing helmets or not. By enforcing helmet regulations, law enforcement agencies can prevent head injuries and mitigate the likelihood of fatal outcomes in the event of accidents.. Helmet detection and number plate detection are two key challenges in computer vision with numerous applications in traffic safety, law enforcement and intelligent transportation systems. Helmet detection is the detection of the presence or absence of motorcycle helmets, which can aid in the prevention of accidents and lower the risk of head injuries. Number plate detection, on the other hand, entails recognising and localising vehicle number plates, which is necessary for identifying and monitor for a variety of reasons such traffic law enforcement. Deep learning-based techniques have showed encouraging results in both helmet recognition and number plate detection tasks in recent years. However, the accuracy and robustness of these methods must be improved in order to address. In this paper, model has been proposed to overcome the limitations of existing state-of-the-art work through the proposed helmet and number plate detection system to reduce road accidents and the fatality rate.

2. BACKGROUND DETAILS

2.1 Impact on society

The impact of helmet detection and number plate detection can be significant in terms of road safety, law enforcement, and transportation systems. Firstly, the implementation of helmet detection can help in reducing minimize the potential for head injuries and mitigate the risk of fatalities. in motorcycle accidents. By enforcing helmet regulations, law enforcement agencies can promote safe riding practices and ensure compliance with safety regulations. Secondly, by recognizing and localizing license plates law enforcement agencies can identify motorcycle involving in accidents, and take necessary actions accordingly. This can help in reducing crime rates, improving traffic flow, and enhancing overall safety and security on the road. This can result in a more streamlined transportation system and better experiences for commuters. Overall, the impact of helmet detection and number plate detection can be significant in terms of promoting road safety, improving law enforcement, and enhancing transportation systems. By implementing these technologies, we can create a safer and more efficient transportation system for all road users.

2.2 Pros & Cons

The implementation of Helmet and number plate detection can also have several benefits. One of the most significant advantages is improved law enforcement. This will lead to automatically detect helmet which will help to automate generate challan. This not only saves time for commuters but also reduces the need for human intervention, which can result in improved efficiency and reduced operational costs.

Despite its potential benefits, helmet detection also has some drawbacks. One of the main concerns is the invasion of privacy, as helmet detection involves capturing images of individuals without their consent. This can raise concerns related to personal data privacy and civil liberties. Another concern is the accuracy of the detection system, as helmet detection relies on computer vision algorithms that may not be 100% accurate. False positives and false negatives may occur, leading to wrongful penalties or non-compliance with safety regulations.

2.3 Algorithm used

The use of deep learning-based approaches has significantly improved the accuracy and speed of object detection tasks, and the You Only Look Once (YOLO) algorithm is one such approach that has gained immense popularity due to its efficiency and accuracy.

YOLO represents a cutting-edge object detection algorithm renowned for its ability to conduct real-time object detection through the utilization of a single neural network. Unlike traditional object detection methods that use a sliding window approach to detect objects, In YOLO, the image is partitioned into a grid, and for each grid cell, the algorithm predicts bounding boxes and class probabilities. This results in a much faster and accurate detection of objects, including helmets and number plates. [2]

3. LITRATURE SURVEY

Romuere et el. (2014) [3] This paper focuses on detecting persons riding two-wheeler, and determining if they are wearing helmets or not. The process involves several steps, starting with the detection of a stable reference background, typically the road, to identify the motion of the vehicles against it. Next, moving objects, which are the vehicles, are separated from the background using background subtraction. The vehicles are subsequently categorized as either motorcycles or non-motorcycles, and a set of distinctive characteristics is constructed for each image, which is then transmitted to a random forest classifier. To detect helmets, a region of interest is determined, reducing processing time and increasing efficiency. From this region, the relevant image containing the head is extracted, and passed through a classifier to determine whether or not the rider is wearing a helmet. However, the project does not detect number plates of the vehicles, which is essential for enforcing penalties on riders without helmets. Overall, this project mainly focuses on helmet detection and can be useful for surveillance systems.

Felix et el. (2019) [4] This paper consists of three divisions aimed at detecting whether a motorcycle rider is wearing a helmet or not. Initially, a diverse dataset comprising videos is gathered from Myanmar and subjected to pre-processing. Each video comprises a sequence of 100 frames. Subsequently, object detection is performed using the YOLO9000 algorithm to identify vehicles, and the specific instances where a person is present in conjunction with a vehicle are encapsulated within bounding boxes. Secondly, the RetinaNet approach is used to detect helmets through object detection, Employing ResNet50 as the foundational architecture, initialized with pre-existing weights derived from the ImageNet dataset, the models were developed using the Python Keras library, with TensorFlow serving as the underlying computational framework. Finally, the results of the helmet detection algorithm are presented, with the optimal model developed on the validation set achieving a weighted mAP of 72.8%. However, a limitation of this project is that it can only detect whether one person on the motorcycle is wearing a helmet or not. In instances where there are two persons on the motorcycle this system lacks the capability to determine whether the passenger seated behind the rider is wearing a helmet or not.. Additionally, the accuracy of the CNN network used in this project is 87%.

Swapna et el. (2019) [5] This paper possesses new technique for automatic helmet detection, which can take input in the form of a recorded video or a video from a web camera. The method involves four steps. Firstly, images of riders on the road are captured using cameras. Then, preliminary processing techniques are employed to eliminate background noise, enhance contrast and perform image binarization. In the third step, vehicles are classified based on their aspect ratio and size. Finally, in the fourth step, the head part of the classified image is extracted and provided to a region of interest (ROI) for matching with trained features to determine whether the rider is wearing a helmet or not. This model can be useful in identifying traffic rule violators and is cost-effective as it utilizes open-source technology such as OpenCV. Moreover, it can be extended to detect drivers who talk on the phone while driving or those who drive at high speeds.

F.A Khan et el. (2020) [6] The proposed framework endeavours to automatically ascertain whether a motorcyclist is wearing a helmet or not through the analysis of images. The system employs the You Only Look Once (YOLO)-Darknet deep learning framework, which integrates Convolutional Neural Networks trained on the Common Objects in Context (COCO) dataset, along with computer vision techniques. The convolutional layers of YOLO are tailored to specifically detect three predetermined classes, and a sliding-window methodology is utilized. By training the model on suitable data, the framework attains a commendable Mean Average Precision (MAP) score of 81% on the validation dataset.

Dasgupta et el. (2019) [7] The proposed framework is designed to detect motorcycle riders who are not wearing helmets, whether there is only one rider or multiple riders. It uses the YOLOv3 model for identifying motorcycle riders and a Convolutional Neural Network (CNN) based architecture for detecting helmets. The model is evaluated on traffic videos, and the results show promising performance compared to other CNN-based approaches. The model's ability to accurately detect helmet use in real-world scenarios could contribute to improving road safety by identifying and penalizing riders who violate helmet laws. Overall, this framework could be an important step towards developing more effective automated systems for detecting and preventing motorcycle accidents caused by a lack of helmet use.

Yoten et el. (2022) [8] The paper proposed a system for license plate detection in motorcyclists involves the implementation of a single convolutional neural network (CNN). The CNN detects the license plate in the video frames and applies the ANPR (Automatic Number Plate Recognition) technology to recognize the characters on the license plate. This allows for further analysis of the information, such as tracking the movement of a specific vehicle. Additionally, to improve the accuracy of helmet detection and reduce the number of false positives, the proposed system incorporates a centroid tracking method. This method is used to track the movement of objects in the video frames and to minimize the occurrence of false positives arising from situations where helmeted bikers are positioned outside the video frame, efforts have been made to enhance the proposed system. Additionally, the system exhibits the capability to detect the license plates of motorcyclists even when they are wearing a hood or cap, further augmenting its functionality., thereby increasing the overall effectiveness of the system in identifying and tracking vehicles.

Sathe et el. (2022) [9] The proposed method employs the YOLOv5 deep learning framework with transfer learning to detect motorcycle riders and their respective helmets. The model utilizes two methods to detect whether the rider is wearing a helmet or not, one being the detection of overlapping between the bounding boxes and the other being the detection of the helmet within the specified region of interest above the motorcycle. The model achieved a mean average precision (mAP) of 0.995, indicating high accuracy in detecting helmeted riders. This approach is unique in that it uses the overlapping method for interlinking objects to determine whether the rider is wearing a helmet. Furthermore, the proposed model is also capable of license plate recognition using EasyOCR. This allows the system to analyze the license plate characters, providing valuable information such as the vehicle's registration details. The use of EasyOCR facilitates the recognition of license plates even when obscured by hoods or caps. The combination of both helmet and license plate detection methods enables traffic police officers to identify and track stolen vehicles, enhancing the efficiency of law enforcement.

Tasbeeha et el. (2023) [10] The proposed system in this paper employs Object Detection using Deep Learning at three levels for identifying and tracking stolen vehicles. At the first level, the YOLOv3 model is used to detect a person with a motorcycle in the input image. Then, at the second level, the YOLOv5 model is utilized to detect whether the person is wearing a helmet or not. Finally, at the third level, YOLOv3 is employed to detect the license plate of the motorcycle. Optical Character Recognition (OCR) is used to extract the registration number from the detected license plate. By using these techniques, the proposed system can detect stolen vehicles from a database and report their location to the authorities. This information can be useful for traffic police officers to track the stolen vehicles and take appropriate action. Moreover, the system can be extended to identify and track other traffic violations, such as over speeding or reckless driving. Object Detection using Deep Learning is a state-of-the-art technique for detecting and localizing objects in an image. The YOLOv3 and YOLOv5 models are popular deep learning models for object detection tasks. YOLOv3 utilizes a single neural network to predict bounding boxes and class probabilities directly from full images in one evaluation, whereas YOLOv5 uses a similar architecture with improved performance and accuracy. OCR is a technique that uses machine learning algorithms to recognize text from images.

4. Proposed Work

4.1 Data Set

For this research, a video data set was used for both helmet detection and number plate detection. The video data set consisted of a collection of traffic surveillance footage captured from various locations. The videos were recorded at different times of the day, under different lighting conditions and included various types of vehicles such as cars, bikes, and buses.

The video data set was challenging because it included cases where riders were wearing different types of turbans or had scarfs around their head. Such instances made it challenging for the model to distinguish between a helmet and a turban or a scarf. Additionally, the dataset also include

instances where the riders were not wearing any headgear, this further complicates the task of discerning whether a rider is wearing a helmet or not, intensifying the challenge for detection algorithms.

4.2 Methodology

4.2.1 Pre-processing:

Before training the YOLO algorithm, the video data set underwent some pre-processing steps to ensure the quality of the data. The video frames were first extracted from the videos and resized to a uniform size of 416x416 pixels. we manually annotated the video frames to mark the regions of interest for both helmet detection and number plate detection tasks.

4.2.2 Modules:

Video input: System takes video footage as input, that will undergo pre-processing module.

Algorithm used: YOLO is used for object detection to identify objects in the video frames, focusing on helmets and number plates.

Object Detection: The object detection module analyses the video frames using the YOLO model to detect objects like helmets and number plates.

4.3 Flowchart

Figure 1 shows the flowchart of the proposed work. The details of each step are discussed below.

1) Start: This is the beginning of the flowchart.

2) Take video input: This step involves opening a pre-recorded video file for processing.

3) Check if next frame can be extracted: Before proceeding, we need to make sure that there are still frames left in the video stream. If there are no more frames, the process stops. Otherwise, we move on to the next step.

4) Extract the frame: If the next frame can be extracted, we proceed to extract it from the video stream.

5) Check for helmet: Once we have the frame, we check if a helmet is detected in the frame. If a helmet is detected, we move on to the next step. If not, we skip ahead to checking for the number plate.

6) Check for number plate: If a helmet is not detected in the frame, we check for a number plate. If a number plate is detected, we generate a challan (traffic violation ticket). If a number plate is not detected, we skip ahead to checking for the next frame.

10) Check for next frame: After generating a challan, we need to check if there are more frames left in the video stream. If there are no more frames, the process stops. Otherwise, we repeat from step 4.

11) Stop: This is the end of the flowchart.

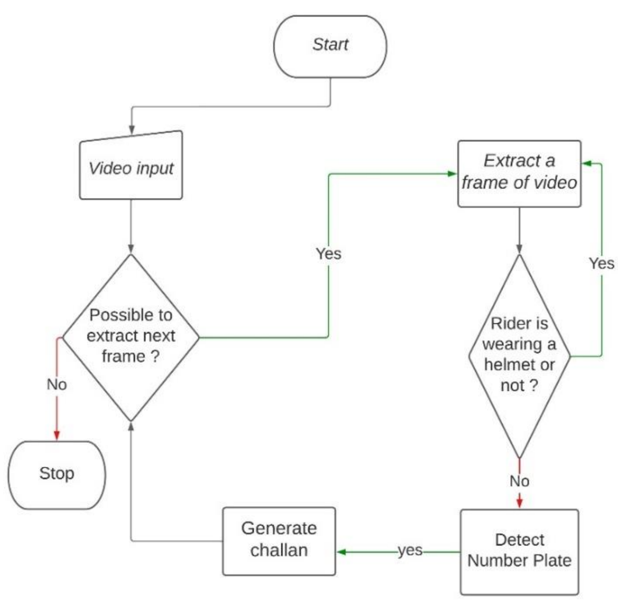


Figure 4: Flowchart of the work

4.4 Algorithm used

The YOLO (You Only Look Once) algorithm is an advanced technique used for real-time object detection and recognition in images. It uses convolutional neural networks (CNN) to accomplish this task, making it a highly efficient and accurate algorithm. What sets YOLO apart from other object detection algorithms is its ability to perform object detection as a regression problem, providing class probabilities for detected images. The algorithm showcases a remarkable characteristic of necessitating only a single forward propagation through the neural network to detect objects encompassing the entire image. This exceptional attribute renders it exceptionally swift and well-suited for real-time applications. YOLO uses the CNN to simultaneously predict class probabilities and bounding boxes, making the algorithm highly accurate and effective. In summary, the YOLO algorithm's remarkable capabilities have made it an essential tool for object detection and recognition in various industries, including self-driving cars, security, and healthcare.

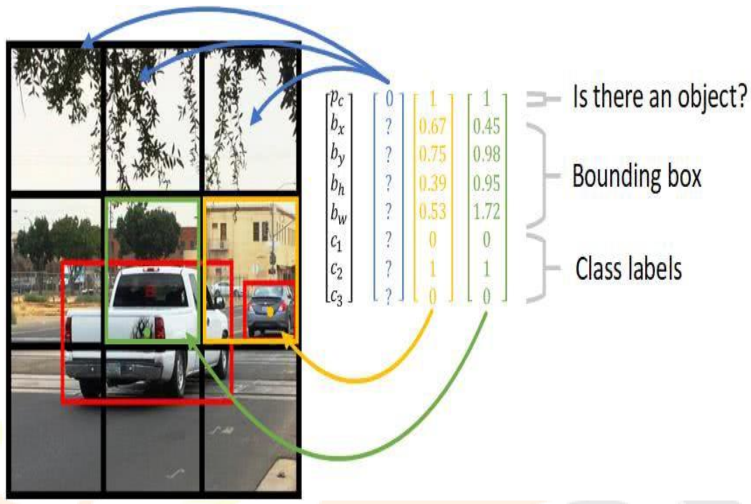


Figure 1: YOLO object detection [11]

4.4.1 Pseudo Code

```
function detect_helmet_and_number_plate(video):
 # Load pre-trained YOLO weights and configuration
 net = load_yolo_weights()
# Loop through video frames
for frame in video:
    # Preprocess frame
     processed_frame = preprocess_frame(frame)
      # Run frame through YOLO model
      output = net.forward(processed_frame)
      # Interpret output predictions
      boxes, classes, confidences = interpret_output(output)
      # Apply non-max suppression to remove redundant boxes
      boxes = apply_nms(boxes, confidences)
# Check for helmet and number plate detections
helmet_detected = False
number_plate_detected = False
for i in range(len(boxes)):
```

```
    if classes[i] == 'helmet' and confidences[i] > 0.5:
        helmet_detected = True
 elif classes[i] == 'number plate' and confidences[i] > 0.5:
 number_plate_detected = True
# Output detection results for current frame
output_detection_results(helmet_detected, number_plate_detected)
```

4.4.2 Intersection over union

Intersection over Union (IoU) serves as a widely employed evaluation metric in object detection endeavors. It quantifies the degree of overlap between the bounding box predicted by the model and the ground truth bounding box of an object. In order to compute the IoU, the initial step involves determining the intersection area between the predicted and ground truth bounding boxes. This intersection area is subsequently divided by the union area of the two bounding boxes, facilitating the computation of the IoU score. The resulting value is the Intersection over Union score. In simpler terms, IoU tells us how well a predicted bounding box overlaps with the ground truth bounding box. A high IoU score indicates that the predicted box is a good match for the ground truth box, while a low IoU score indicates a poor match. IoU is a valuable metric for evaluating the performance of object detection models, as it provides an objective measure of how accurate the predictions are. It is commonly used in tasks such as object tracking, where it is important to accurately identify and locate objects in real-time.

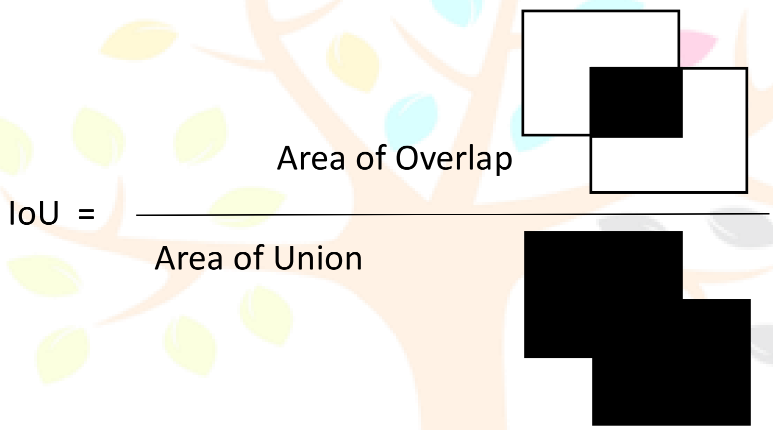


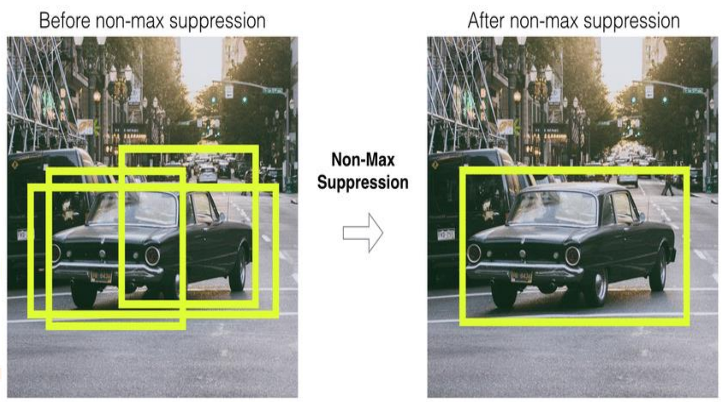
Figure 2: Diagrammatic representation of IOU

```
# Compute Intersection over Union for helmet detections
max_iou = 0.0
for i in indices:
    if classes[i] == 'helmet' and confidences[i] > 0.5:
        iou = compute_iou(boxes[i], helmet_ground_truth)
            if iou > max_iou:
                max_iou = iou
# Determine if helmet is detected based on IoU threshold
        if max_iou > 0.5
            helmet_detected = True
        else
            helmet_detected = False
```

4.4.3 non-Max suppression

Non-Max suppression is a post-processing technique used in object detection to eliminate redundant and overlapping bounding boxes. In object detection, an algorithm may generate multiple bounding boxes for a single object due to variations in scale, orientation, and lighting conditions. Max suppression helps to filter out these redundant bounding boxes and keep only the most accurate one. The max suppression algorithm works by comparing the Intersection over Union (IoU) scores of each pair of bounding boxes. If the IoU score is above a specified threshold, one of the bounding boxes is removed based on its confidence score. The algorithm iteratively compares all bounding boxes, removing those with high overlap until there are no more overlapping boxes left. This results in a set of non-overlapping bounding boxes, which represent the object locations in the image. Max suppression is an essential component in object detection algorithms, as it helps to improve the accuracy and reduce false positives in the output. It is commonly used in state-of-the-art object detection models, such as YOLO and SSD.

Figure 3: Demonstration of Non max suppression [12]



4.4.4 Combination of above techniques

The process of object detection involves dividing an image into smaller sections called grid cells. Within each grid cell, a neural network predicts the presence of objects by generating bounding boxes that define the objects' location in the image. The neural network produces confidence scores for each bounding box, which indicate the network's level of certainty that the bounding box accurately represents an object in the image. In addition to bounding boxes, the network also predicts the probability of each detected object belonging to a specific class. For example, in an image of a street scene, objects could include cars, pedestrians, and bicycles. The network will estimate the probability of each detected object belonging to the respective classes. The grid cells provide a flexible approach to detecting objects of various sizes, shapes, and orientations. The network can predict multiple bounding boxes per grid cell, increasing the likelihood of accurately detecting an object in the image. By combining the confidence scores and class probabilities of each predicted bounding box, the network produces a final output that identifies the objects present in the image and their respective locations.

5. Results and discussion

The results of this study suggest that the YOLO algorithm is a highly effective method for helmet and number plate detection in real-world scenarios. The high accuracy, precision, and recall values achieved by the algorithm demonstrate its potential for use in a range of applications, including traffic management, law enforcement, and safety monitoring.

There were some limitations to this study, however. The dataset utilized for training and testing the algorithm was relatively diminutive in scale, potentially constraining the extent to which the results can be extrapolated and applied to broader scenarios.

When we give video as an input, it successfully detects whether the rider is using helmet or not, also it successfully detects the number plate.

Below are the screenshots of the results that are obtained from the detection of helmet and number plate using YOLO algorithm.

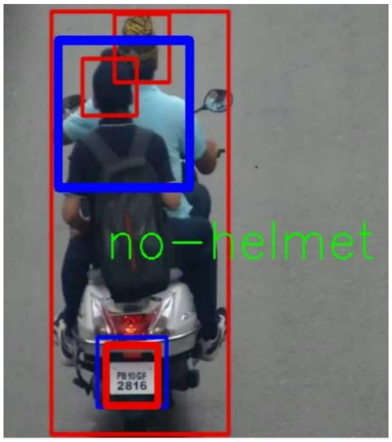


Figure 5: No helmet for rider & Pillion

Figure 6: Helmet detected for rider

Figure 7: Pillion not wearing helmet

In Figure 5, the detection of helmets for both the pillion and the rider is depicted. When neither the pillion nor the rider is wearing a helmet, a red box is drawn around them. In Figure 7, the rider is shown wearing a helmet, indicated by a green box surrounding their head. However, the pillion is not wearing a helmet, as evidenced by the red box surrounding their head, indicating that no helmet is detected for them. Whereas when the rider wearing helmet and there is no pillion then green box is drawn which indicate that the helmet is detected, same case is indicated in figure 6.

5.1 Comparative Analysis

Machine and deep learning algorithms are highly powerful and versatile, exhibiting remarkable capabilities in recognizing helmets within images or videos. To tackle this task, four distinct models are studied: a customized Convolutional Neural Network (CNN), Support Vector Machine (SVM), k-nearest neighbours (KNN), and decision tree. Each of these models is utilized on the dataset to accomplish the desired objective of helmet detection.

Table 1: Comparation of the model on the basis of accuracy

Model	Accuracy
Decision tree [3]	80%
SVM [5]	85.28%
KNN [6]	81.82%
CNN [4]	87%
Proposed work CNN(YOLO)	95.42%

Based on the comparation of model in table 1 and figure 9, represents that support vector machine and decision tree are not the good choice for helmet detection as they have very low accuracy. Whereas k nearest algorithm and CNN has very good accuracy.

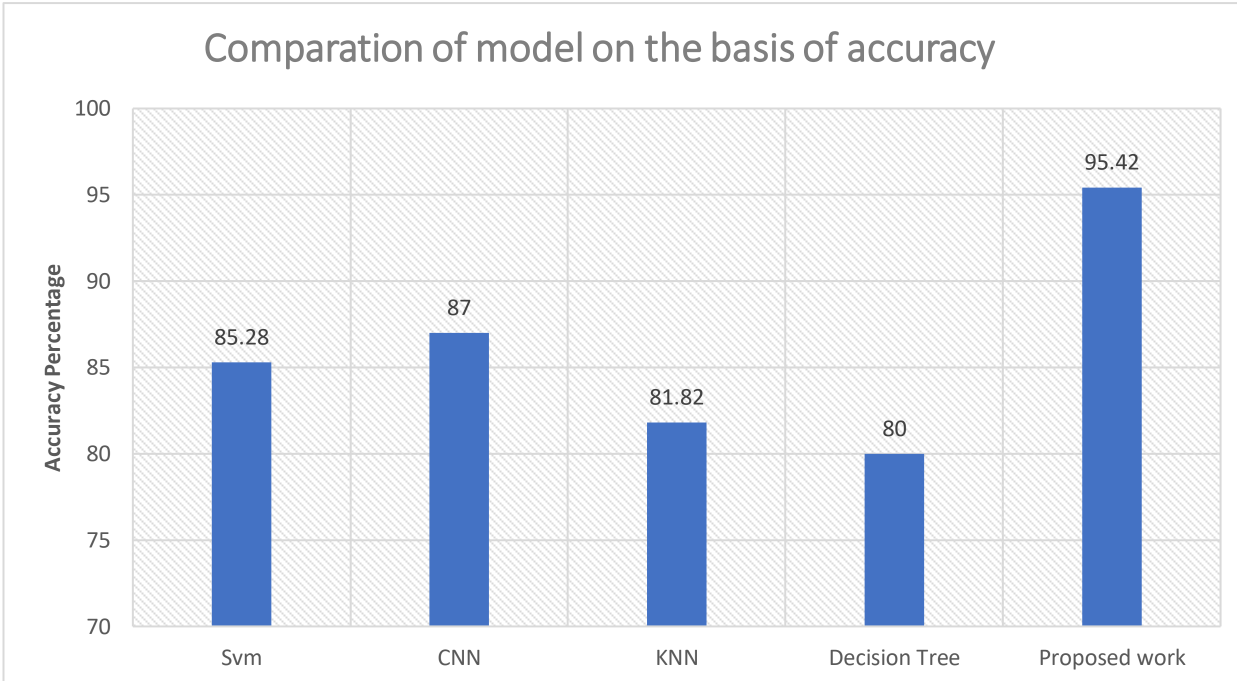


Figure 9: Graphical representation of model on the basis of accuracy

Table 2: Comparation between different algorithm based on CNN

Name of Algorithm	Speed	Accuracy	Accuracy speed trade-off	Multiple Detection
Haar Casde Classifier	Fast	Not good	Yes	No
Faster R CNN	Fast	Very Good	No	Yes
SSD	Slow	Not Good	No	No
YOLO	Fast	Good	Yes	Yes

Based on the comparation between different algorithm in table 2, it shows that YOLO has strong performance in object detection tasks. It has a good balance between accuracy and speed. Compared to the Haar Cascade Classifier, YOLO tends to provide higher accuracy. Haar Cascade Classifier heavily relies on handcrafted features, which can limit its ability to accurately detect complex objects like helmets and number plates, particularly under challenging conditions. On the other hand, YOLO leverages deep convolutional neural networks, allowing it to learn more expressive features and capture object details effectively. In comparison to other advanced algorithms like Faster R-CNN , YOLO offers faster inference times while still maintaining a competitive level of accuracy. Faster R-CNN and Mask R-CNN perform well in terms of accuracy but tend to be slower due to their multi-stage architectures and pixel-wise segmentation capabilities. Considering the balance between accuracy and speed, YOLO is often considered a reliable choice for helmet and number plate detection tasks. It provides good accuracy, and making it suitable for applications that require both efficiency and accuracy.

6. Conclusion

The detection of helmets and number plates is crucial for ensuring road safety, as many individuals tend to overlook their importance. To address this issue, an automated method is needed to determine whether riders and pillion passengers are wearing helmets. By employing machine learning techniques, we can not only automate the system but also save significant time.

In this study, we propose a solution that utilizes the YOLO algorithm based on Convolutional Neural Networks (CNN) for helmet and number plate detection. This advanced deep learning approach has yielded highly satisfactory outcomes, demonstrating promising results in accurately detecting helmets and recognizing license plates in real-time scenarios. With the implementation of the YOLO algorithm, the model efficiently processes video frames by dividing them into grid cells and predicting bounding boxes and class probabilities for each cell. As a result, the model can determine whether a rider is wearing a helmet with a commendable level of accuracy.

Furthermore, we compared our proposed model with other algorithms like SVM, KNN, and Decision Tree, which achieved accuracies of 85.28%, 81.82%, and 80% respectively. In contrast, our proposed approach attained an impressive accuracy of 95.42%.

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