IJIRMET ISSN (Online): 2456-0448
International Journal Of Innovative Research In Management, Engineering And Technology
Vol. 9, Issue 3, April 2024

Traffic Violation Prediction Using Deep Learning Based On Helmets with Number Plate Recognition

[1] Dr.E.Punarselvam, [2] T.Harshini, [3] N.Manochitra, [4] T.Parimala
[1] Professor, Department of Information Technology, Muthayammal Engineering College (Autonomous), Rasipuram-637 408
[2] [3] [4] Final Year Students, Department of Information Technology, Muthayammal Engineering College (Autonomous), Rasipuram-637 408

Abstract: ***Two-wheelers are currently the most popular form of transportation. Helmet wearing is extremely recommended for both bike riders and the pillions. Object tracking in video surveillance is of great interest for many researchers, which is an important application and emerging research area in machine learning and image processing. Detecting object is a process to find the presence of objects with a bounding box and categories or forms of the placed objects in a picture. This paper provides a review on tracking techniques, their categorization into different types and focuses on important and useful tracking techniques. We review general strategies under literature survey on different techniques and finally state the analysis of possible research directions. This study employs an image processing algorithm to identify motorbike riders who are not wearing helmets. And also implement Optical Character Recognition algorithm for classify the number plate in image and extract the user details. Then calculate the fine amount. Finally making SMS services to send alert the users too preventing motorcycle accident. We assess the framework as far as accuracy and speed.***

KEYWORDS: Number plate Recognition, Object detection, Object Recognition, Optical Character recognition, Traffic Violations

I. INTRODUCTION

Since accidents and injuries are more likely to occur as a result of the increasing congestion on our roads in the modern world, traffic safety is of utmost importance. Helmets have long been associated with safety and protection for cyclists and motorcyclists. But helmets' significance goes beyond simple symbolic; they are essential for lessening the severity of brain injuries sustained in accidents. Governments and law enforcement organisations have therefore established stringent helmet-wearing laws to improve road safety. We will examine the relevance of helmet traffic offences, the justifications for these laws, and the possible repercussions for both individuals and society when helmet laws are disregarded in this debate. The fundamental objective of helmet regulations is to protect the lives and wellbeing of riders of motorcycles, bicycles, and other two-wheeled vehicles. In order to ensure that the head and brain are appropriately protected in the case of an accident, these regulations frequently demand that riders wear helmets that adhere to strict safety standards. Helmets are an essential part of road safety since they have been shown to drastically lower the risk of fatalities and head injuries in motorcycle accidents. Detecting helmets in images and video streams is a critical application in numerous safety-critical domains, including construction sites, sports facilities, and road traffic. This technology leverages image processing and machine learning techniques to identify individuals wearing helmets, ensuring compliance with safety regulations and enhancing overall safety. Figure 1 shows the helmet detection system by police in real time system

Figure 1: Police Intervention for Helmet detection

II. RELATED WORK

Susa, Julie Ann B, et.al,…[1] proposed vision-based system could aid in identifying riders who are wearing helmets that aren't fitting properly. The system used the YOLOv3 model and a deep learning approach to use the helmet detection model in this work. Creating multiple checkpoints to monitor riders for helmets may cause traffic congestion on many public roadways. It is necessary to establish an early detection system for their safety to prevent accidents and to follow the law of wearing authorized helmets. The YOLOv3 approach will be employed in this research. The system scored 90 % above for all of the testing features as a consequence of testing and deployment.

Waris, Tasbeeha, et al,…[2]developed a system for automatically detecting bikers without a helmet using a faster region-based convolutional neural network (R-CNN). (e system takes input in the form of video and converts that into frames to perform helmet violation detection. (e dataset has been collected from two sources, i.e., online repositories and self-captured videos from different locations in Lahore, Pakistan. (e experimental analysis shows that the proposed system has 97.69% accuracy. It may help to take necessary actions against traffic rule violators. (is work may be extended to incorporate more features, like number plate detection and other traffic violations, in the future.

Tran, Duong Nguyen-Ngoc, et al,…[3]presents a framework to detect and identify separate motorcycles while tracking riderspecific helmet use. The helmet-use classification approach shows increased efficiency compared to previous studies. This approach builds on and extends a previous framework, taking advantage of new techniques and algorithms to achieve even greater accuracy and precision. By incorporating state-of-the-art technologies and best practices, we have created a powerful tool for detecting helmet use in various scenarios and settings. This approach will prove to be an invaluable resource for promoting motorcycle safety and reducing the number of preventable injuries and fatalities.

Deng, Lixia, et al,…[4]proposes a lightweight object detection network: ML-YOLOv3. In this paper, three network improvement methods are proposed, which can significantly reduce the computational cost of the model while maintaining a strong detection effect. Based on the helmet dataset, CSP-Ghost-ResNet proposed by us effectively reduces the complexity of the model and achieves almost the same level of detection effect as YOLOv3. ML-Darknet reduces the detection effect of the model, but it effectively reduces the computational cost of the model. In addition, PAN-CGR-Network is redesigned in this paper. It further reduces computing costs.

An, Qing, et al,…[5]proposed a modified YOLOv5 network to adaptively adjust the anchor box to increase the matching degree between the anchor box and the target box, which can extract discriminative image features from small targets. In the proposed method, the GAM attention mechanism is combined with the CPS module of the CBAM attention mechanism. It is added to the backbone network (Backbone) and neck network (Neck) of the original YOLOv5s network to improve the performance of the neural network by reducing the loss of feature information and amplifying the global interaction. This article introduces a three-dimensionally arranged channel attention and convolutional spatial attention sub-module with a multi-layer perceptron, and the feature map adaptively refines each convolutional block of the network structure through a combination module, which is conducive to the establishment of high dimensional spatial feature correlation and the extraction of effective features of the target.

Hayat, Ahatsham, et.al,…[6]used different versions of YOLO architecture, YOLOv3, YOLOv4, and YOLOv5x, to detect safety helmets due to their proven accuracy in object detection tasks. Among them, YOLOv5x achieved the best mAP (92.44%) in detecting smaller objects and objects in low-light images, thereby showing its efficacy in safety helmet detection. Despite the significant outcomes achieved by YOLOv5x-based architecture, it also possesses several limitations. The proposed deep learning model struggled to perform in some scenarios (e.g., with an obstacle in front of helmets, and objects identical to helmets). Training the model with more images, including the above-mentioned scenarios, could potentially increase the model's efficacy. Moreover, in the future, more safety tools could be added for detection, such as vests, gloves, and glasses, to ensure greater safety for workers

Song, Hongru,et.al,…[7]propose a parallel RSSEnetwork module to replace the Res8 module in Darknet53. It can increase the network width, reduce the network depth, and improve the network speed and the detection accuracy of small targets in the model; Then propose using residual module Res2 to replace CBL×5 modules in the YOLOv3 algorithm. This scheme can avoid gradient disappearance and enhance the reuse of features, improving the accuracy of detecting dense target occlusion; And propose increasing the resolution of the input image to 608 × 608, and increasing the output feature map from three-scale detection to four-scale detection, which can improve the accuracy of the model for small target detection; The ablation experiments on the helmet dataset show that the RSSE-YOLOv3 algorithm proposed in this paper has improved the detection performance.

Chen, Junhua, et al,…[8] proposes an improved YOLOv4 algorithm to achieve real-time and efficient safety helmet wearing detection. The improved YOLOv4 algorithm adopts a lightweight network PP-LCNet as the backbone network and uses deep wise separable convolution to decrease the model parameters. Besides, the coordinate attention mechanism module is embedded in the three output feature layers of the backbone network to enhance the feature information, and an improved feature fusion structure is designed to fuse the target information. In terms of the loss function, we use a new SIoU loss function that fuses directional information to increase detection precision. However, accidents arising from workers not wearing safety helmets can be seen everywhere due to a lack of a particular sense of safety protection. Therefore, monitoring whether workers are wearing helmets is crucial to their safety. Traditional helmet inspection mainly consists of monitoring in the surveillance room and manual patrol at the construction site. The former requires inspectors to stare at the screen for long periods, which can cause eye fatigue and lead to misjudgements and missed inspections, while the latter requires a lot of time and labor. Motivated by this, new methods for detecting the wearing of safety helmets by construction site workers are rapidly emerging with the help of sensors and image analysis techniques

Tsai, Chun-Ming, et al,…[9]presented two new deep learning models, YOLOv7-CBAM and YOLOv7-SimAM, which incorporate YOLOv7-E6E, CBAM, and SimAM. The YOLOv7- E6E model was trained on images of size 1920, while the YOLOv7-CBAM and YOLOv7-SimAM models were trained on images of size 1280. These models were employed to detect the test images in Track 5, and the results were submitted to the AI City CHALLENGE Track 5 evaluation system. The experimental results on the 100 test videos of the 2023 AI City CHALLENGE Track 5 demonstrate the effectiveness of our methods, with mAP scores of 0.6112, 0.6389, and 0.6422 for YOLOv7-E6E, YOLOv7-CBAM, and YOLOv7-SimAM, respectively. Our proposed methods ranked sixth, fifth, and fourth on the public leaderboard, out of over 36 participating teams. However, YOLOv7-CBAM produced one false positive motorbike and two false positive DHelmets. Overall, the proposed models demonstrate the potential of deep learning techniques in improving traffic safety measures, and they highlight the importance of continued research in this area. The code for these models is publicly available, enabling others to build upon these advancements and further improve the state-of-the-art

] Aboah, Armstrong, et al,…[10] proposed and implemented a novel data processing strategy, called the ”few-shot data sampling technique”, for developing a robust helmet detection model with fewer annotations. The technique involves selecting a small but representative number of images from a large dataset using our developed algorithms and then applying data augmentation techniques to generate additional images for training. By using this technique, we able to develop a robust helmet detection model with fewer annotations, which is an important contribution as it reduces the time and effort required for annotation. Developed a real-time helmet detection system that is robust to varying weather conditions and time of day by utilizing YOLOv8, a state-of-the-art object detection model, and data augmentation techniques. YOLOv8 is designed to be fast and accurate, making it ideal for use in real time. In addition, several data augmentation strategies were utilized in this study to overcome the issues of occlusion and viewpoint problems. To further improve prediction accuracy and confidence during inference time, the study employed test time augmentation (TTA) during its inference stage.

III. EXISTING METHODOLOGIES

Nowadays, road accidents are one of the major causes that lead to human death. Motorbike accidents can cause severe injuries. The helmet is important for every motorcyclist. However, many fail to conform to the law of wearing helmets. Helmets are essential equipment’s to protect workers from danger during inspection and operation. Considering that some workers would not always obey the regulation, video surveillance systems covering the whole factory and supervisors are needed to monitor whether workers are wearing helmets or not. However, with a large number of surveillance screens, it is difficult to identify any helmet violation behaviour during any time, which can lead to severe accidents. With the rapid development of image recognition technologies, computer vision-based inspections have been one of the most important industrial application areas. Existing system focuses on monitoring whether workers are wearing helmets or not, at the same time, identifying the colors of helmets. A color-based hybrid descriptor composed of local binary patterns (LBP), hu moment invariants (HMI) and color histograms (CH) is proposed to extract features of helmets with different colors (red, yellow and blue). Then a hierarchical support vector machine (H-SVM) is constructed to classify all features into four classes (red-helmet, yellow-helmet, blue helmet and non-helmet).

3.1 LOCAL BINARY PATTERN FOR HELMET DETECTION

Local Binary Patterns (LBP) is a texture analysis technique that can be utilized for helmet detection in images. LBP is known for its robustness in describing the local texture patterns in an image, making it suitable for detecting the texture of helmets in various scenes. LBP operates by comparing the intensity of a pixel with its neighbouring pixels. For each pixel in the image, a binary code is generated based on whether the neighbouring pixels have intensities greater or less than the central pixel. The binary code is then converted to a decimal value. For helmet detection, LBP can be applied to extract texture features from a region of interest (ROI) around the head area, which may include the helmet. This feature extraction process characterizes the local texture patterns within the ROI. Collect a dataset of labeled images that includes images of individuals wearing helmets and individuals without helmets. These images serve as the training data for your LBP-based helmet detection model.

3.2 HU-MOMENT INVARIATIONS

Hu Moment Invariants (HMI) are a set of mathematical descriptors used in image processing and computer vision to characterize the shape and spatial distribution of an object in a binary or grayscale image. These moment invariants are invariant to translation, scale, and rotation, making them valuable for shape analysis and object recognition.

Hu Moment Invariants are denoted as H1, H2, H3, H4, H5, H6, and H7, and they are calculated from the central moments of an image. Here is a brief explanation of each Hu Moment Invariant:

- H1 (Invariant to Scale): Measures the overall intensity of the image. It is invariant to scale changes in the object.
- H2 (Invariant to Rotation): Describes the skewness and orientation of the object. It remains unchanged when the object is rotated.
- H3 (Invariant to Rotation): Represents the balance or elongation of the object. Like H2, it is invariant to object rotation.
- H4 (Invariant to Scale and Rotation): Measures the fourth moment of the distribution of the object's pixel intensities, making it invariant to both scale and rotation.
- H5 (Invariant to Scale): Measures the compactness of the object. It is invariant to scale transformations.
- H6 (Invariant to Scale and Rotation): Represents the object's skewness. It is invariant to scale changes and rotations.
- H7 (Invariant to Scale): Measures the elongation or thinness of the object. It remains unchanged under scale transformations.

For helmet detection, Hu Moment Invariants can be used to characterize the shape and orientation of helmets, making it possible to distinguish helmets from other objects or background in images. By comparing the computed HMI of a region of interest (ROI) with pre-determined values for helmets, it can assist in identifying individuals wearing helmets, ensuring compliance with safety regulations.

3.3 COLOR HISTOGRAMS BASED OBJECT DETECTION

Color histograms are statistical representations of the distribution of colors in an image. They provide valuable information about the presence and abundance of various colors within an image. Color histograms are widely used in image processing and computer vision for tasks such as image retrieval, object detection, image segmentation, and more. A color histogram divides the color space into discrete bins. For an 8-bit color space (e.g., RGB with 256 intensity levels for each channel), there can be 256 bins per channel. The number of bins can vary, and it influences the granularity of the color distribution information. For each channel (e.g., Red, Green, and Blue), the image is scanned, and the color values for each pixel are assigned to their corresponding bin. The histogram counts how many pixels fall into each bin. To make histograms comparable across different images, it is common to normalize them. This involves dividing the count in each bin by the total number of pixels in the image, creating a probability distribution.

3.4 SUPPORT VECTOR MACHINE FOR HELMET DETECTION

Support Vector Machine (SVM)-based approach for helmet detection, which is designed to automatically identify individuals wearing helmets in images or video streams. The system is built on a foundation of machine learning, with an emphasis on robust feature extraction and real-time processing. The methodology begins with data collection and preprocessing, ensuring that images are consistent and ready for analysis. Feature extraction techniques, including color histograms and shape-based features, are employed to represent the key characteristics of helmets. The dataset is divided into training and testing sets, enabling the SVM model to learn and generalize from a diverse range of helmet and non-helmet examples. Model evaluation metrics, such as accuracy, precision, recall, and F1 score, are used to assess its performance. In real-time applications, the trained SVM classifier processes images or video frames, classifying individuals as either wearing helmets or not.

IV. PROPOSED METHODOLOGIES

There is no automated existing system which can detect motorcyclists who are not wearing helmets as well as masks due to which the traffic policemen have to manually keep records of such traffic rules violators either by remembering the number plate or by capturing a photo of the number plate. This manual administration can sometimes lead to errors. In order to overcome these drawbacks, we have designed an automated helmet and face mask detection system which is able to catch all the motorcyclists who are not wearing helmets and masks just by storing the number plate of those bike riders. To overcome the disadvantages of the existing system, we have proposed an automated system which is more accurate and requires minimum human efforts. The main application of this system is to catch all the motorcyclists who are not wearing helmets. In this paper, implement the framework to identify the helmet traffic violations in real time environments. We can use object detection and recognition system to identify the helmet using YOLO algorithm. And also recognize the number plate using Convolutional neural network algorithm to extract user details. The proposed approach is able to detect the object

IJIRMET ISSN (Online): 2456-0448
International Journal Of Innovative Research In Management, Engineering And Technology
Vol. 9, Issue 3, April 2024

in different illumination and occlusion. The system extracts objects class based on feature extracted. The system uses You Only Look Once (YOLO)-Darknet deep learning framework which consists of Convolutional Neural Networks trained on Common Objects in Context (COCO) and combined with computer vision. Based on CNN, we can detect the text object and recognize the objects to print the number plate. The Send fine amount as SMS to non-wearing helmet persons. Then check the fine amount paid status and updated in database. If user not pay the amount means, automatically block the number and send notification about the status. Admin can renew the number plate after received the amount. Fig 2 display overall architecture of proposed system.

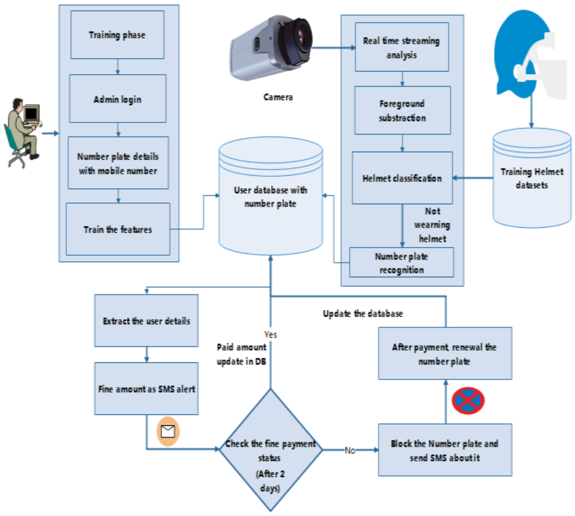

Fig 2: Proposed architecture

4.1 YOLO ALGORITHM FOR HELMET DETECTION

YOLO is an algorithm that uses neural networks to provide real-time object detection. This algorithm is popular because of its speed and accuracy. It has been used in various applications to detect traffic signals, people, parking meters, and animals.

YOLO algorithm works using the following three techniques:

Residual blocks

- A bounding box is an outline that highlights an object in an image.
- Every bounding box in the image consists of the following attributes:
- Width (bw)
- Height (bh)
- Class (for example, person, car, traffic light, etc.)- This is represented by the letter c.
- Bounding box center (bx,by)

Bounding box regression

- Bounding box regression
- A bounding box is an outline that highlights an object in an image.
- Every bounding box in the image consists of the following attributes:
- Width (bw)
- Height (bh)
- Class (for example, person, car, traffic light, etc.)- This is represented by the letter c.
- Bounding box center (bx,by)

Intersection Over Union (IOU)

- Intersection over union (IOU) is a phenomenon in object detection that describes how boxes overlap. YOLO uses IOU to provide an output box that surrounds the objects perfectly.
- Each grid cell is responsible for predicting the bounding boxes and their confidence scores. The IOU is equal to 1 if the predicted bounding box is the same as the real box. This mechanism eliminates bounding boxes that are not equal to the real box

Based on feature, provide the label about objects with improved accuracy rate.

4.2 NUMBER PLATE RECOGNITION

Number plates are utilized as distinguishing proof of vehicles everywhere throughout the countries. The number plate recognition system uses a picture handling technique for perceiving automobiles by their number plates. Number plate recognition systems are utilized with the point of viable movement control and security applications like access control to limited regions and pursue wanted vehicles.

The detected number plate follows subsequent steps:

1.To capture image of number plate

2. To segment and recognize characters.

3.Recognised license plate displays on graphical user interface and stored in database with time and date for further use

4. Send fine amount to user as SMS

4.2.1 OPTICAL CHARACTER RECOGNITION

Optical Character Recognition (OCR) has been a topic of interest for many years. It is defined as the process of digitizing a document image into its constituent characters. Despite decades of intense research, developing OCR with capabilities comparable to that of human still remains an open challenge. Due to this challenging nature, researchers from industry and academic circles have directed their attentions towards Optical Character Recognition. Over the last few years, the number of academic laboratories and companies involved in research on Character Recognition has increased dramatically. This research aims at summarizing the research so far done in the field of OCR. Optical Character Recognition (OCR) is a piece of software that converts printed text and images into digitized form such that it can be manipulated by machine. Unlike human brain which has the capability to very easily recognize the text/ characters from an image, machines are not intelligent enough to perceive the information available in image. Therefore, a large number of research efforts have been put forward that attempts to transform a document image to format understandable for machine. OCR is a complex problem because of the variety of languages, fonts and styles in which text can be written, and the complex rules of languages etc. Hence, techniques from different disciplines of computer science (i.e. image processing, pattern classification and natural language processing etc. are employed to address different challenges. An OCR is not an atomic process but comprises various phases such as acquisition, pre- processing, segmentation, feature extraction, classification and post-processing. Each of the steps is discussed in detail in this paper. Using a combination of these techniques, an efficient OCR system can be developed as a future work. The OCR system can also be used in different practical applications such as number-plate recognition, smart libraries and various other real-time applications.

V. EXPERIMENTAL RESULTS

Helmet images are collected from KAGGLE datasets. The real time helmet detection with number plate recognition done by using Python code.

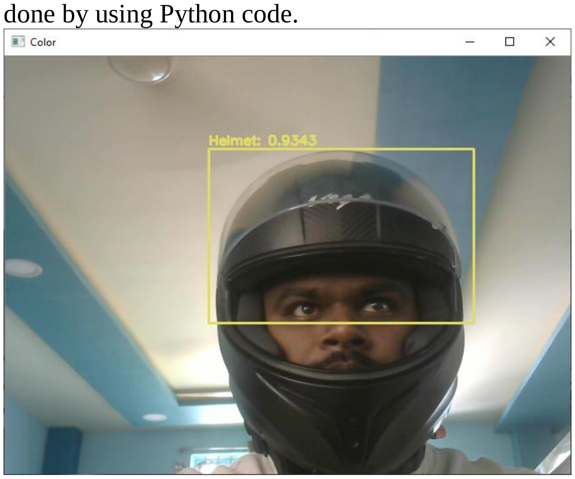

Fig 3: Helmet detection

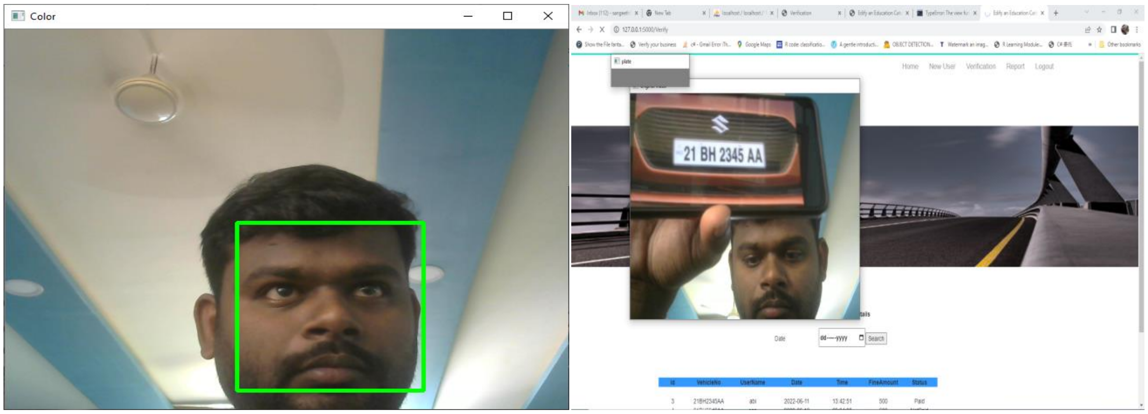

Fig 4: Number plate recognition (Without Helmet)

Different performance measures such as accuracy, sensitivity, specificity, error rate and precision can be derived for analyzing the performance of the system.

- True positive (TP): number of true positives - perfect positive prediction
- False positive (FP): number of false positives - imperfect positive prediction
- True negative (TN): number of true negatives - perfect negative prediction
- False negative (FN): number of true negatives - imperfect negative prediction

Error rate

Error rate (ERR) is computed as the fraction of total number of imperfect predictions to the total number of test data. The finest possible error rate is 0.0, whereas the very worst is 1.0. Minimization of this error rate will be the prime objective for any classifier.

$$ERR = \frac{FP + FN}{TP + TN + FN + FP}$$

ALGORITHM	ERROR RATE
RANDOM FOREST	0.75
SUPPORT VECTOR MACHINE	0.5
YOLO ALGORITHM	0.4

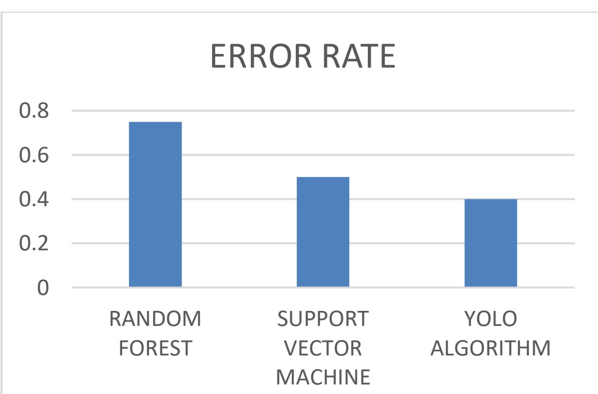

Fig 3: Error rate

From the above graph, proposed YOLO algorithm provide less error rate than the existing algorithm

Accuracy: Accuracy (ACC) is found as the fraction of total number of perfect predictions to the total number of test data. It can also be represented as 1 – ERR. The finest possible accuracy is 1.0, whereas the very worst is 0.0.

$$ACC = \frac{TP+TN}{TP+TN+FN+FP} \text{ x } 100$$

ALGORITHM	ACCURACY
RANDOM FOREST	50%
SUPPORT VECTOR MACHINE	65%
YOLO WITH OCR	80%

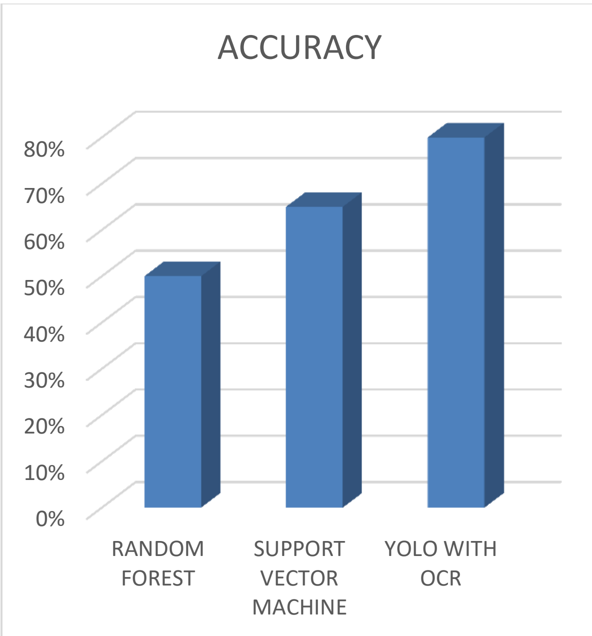

Fig 4: Accuracy chart

From the above graph, proposed YOLO with CNN algorithm provide high level accuracy rate than the existing algorithm

VI. CONCLUSION

In this paper we have described various algorithms for helmet detection and existing system only support the image datasets for helmet analysis. So, we can propose system for automatic detection of motorcycle riders without helmet from real time camera capturing and automatic retrieval of vehicle license number plate for such motorcyclists. The use of YOLO and OCR will help in achieving good accuracy for detection of motorcyclists not wearing helmets. But, only detection of such motorcyclists is not sufficient for taking action against them. So, the system will also recognize the number plates of their motorcycles and store them. In this project, we have used the YOLO for identification of real time person with and without helmets. YOLO is suitable to detect the single object from the image, YOLO has a limitation that if there are multiple objects in a single cell then YOLO is not suitable to all objects. And also accomplished deep learning based automatic license plate recognition model for Indian road users. Results denote that the preferred technique perform better than the existing methods by far in energizing datasets of Indian fonts with high irregularities, containing Number plates and successfully created a custom dataset of Indian font variants Successfully trained the model with Sequential CNN algorithm. The stored number plates can be then used by Transport Office to get information about the motorcyclists from their database of licensed vehicles. Concerned motorcyclists can then be penalized.

REFERENCES

[1] Susa, Julie Ann B., et al. "An efficient safety and authorized helmet detection using deep learning approach." 2022 International Conference on Smart Information Systems and Technologies (SIST). IEEE, 2022..

[2] Waris, Tasbeeha, et al. "CNN-Based Automatic Helmet Violation Detection of Motorcyclists for an Intelligent Transportation System." Mathematical Problems in Engineering 2022 (2022).

[3] Tran, Duong Nguyen-Ngoc, et al. "Robust automatic motorcycle helmet violation detection for an intelligent transportation system." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2023.

[4] Deng, Lixia, et al. "A lightweight YOLOv3 algorithm used for safety helmet detection." Scientific reports 12.1 (2022): 10981.
[5] An, Qing, et al. "Research on safety helmet detection algorithm based on improved YOLOv5s." Sensors 23.13 (2023): 5824.
[6] Hayat, Ahatsham, and Fernando Morgado-Dias. "Deep learning-based automatic safety helmet detection system for construction safety." Applied Sciences 12.16 (2022): 8268.
[7] Song, Hongru. "Multi-scale safety helmet detection based on RSSE-YOLOv3." Sensors 22.16 (2022): 6061.
[8] Chen, Junhua, et al. "Lightweight helmet detection algorithm using an improved YOLOv4." Sensors 23.3 (2023): 1256.
[9] Tsai, Chun-Ming, et al. "Video analytics for detecting motorcyclist helmet rule violations." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2023.
[10] Aboah, Armstrong, et al. "Real-time multi-class helmet violation detection using few-shot data sampling technique and yolov8." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2023.
[11] J. Cao, Y. Pang, J. Xie, F. S. Khan, and L. Shao, ‘‘From handcrafted to deep features for pedestrian detection: A survey,’’ IEEE Trans. Pattern Anal. Mach. Intell., vol. 44, no. 9, pp. 4913–4934, Sep. 2022.
[12] S. Srivastava, S. Narayan, and S. Mittal, ‘‘A survey of deep learning techniques for vehicle detection from UAV images,’’ J. Syst. Archit., vol. 117, Aug. 2021, Art. no. 102152
[13] A. Dosovitskiy, L. Beyer, A. Kolesnikov, D. Weissenborn, X. Zhai, T. Unterthiner, M. Dehghani, M. Minderer, G. Heigold, S. Gelly, J. Uszkoreit, and N. Houlsby, ‘‘An image is worth 16×16 words: Transformers for image recognition at scale,’’ 2020, arXiv:2010.11929.
[14] Z. Liu, Y. Lin, Y. Cao, H. Hu, Y. Wei, Z. Zhang, S. Lin, and B. Guo, ‘‘Swin transformer: Hierarchical vision transformer using shifted windows,’’ in Proc. IEEE/CVF Int. Conf. Comput. Vis. (ICCV), Oct. 2021, pp. 9992–10002.
[15] A. Chairat, M. N. Dailey, S. Limsoonthrakul, M. Ekpanyapong, and D. Raj K. C., ‘‘Low cost, high performance automatic motorcycle helmet violation detection,’’ in Proc. IEEE Winter Conf. Appl. Comput. Vis. (WACV), Mar. 2020, pp. 3549–3557.
[16] F. W. Siebert and H. Lin, ‘‘Detecting motorcycle helmet use with deep learning,’’ Accident Anal. Prevention, vol. 134, Jan. 2020, Art. no. 105319
[17] Z. Cai and N. Vasconcelos, ‘‘Cascade R-CNN: High quality object detection and instance segmentation,’’ IEEE Trans. Pattern Anal. Mach. Intell., vol. 43, no. 5, pp. 1483–1498, May 2021
[18] A. Goyal, D. Agarwal, A. Subramanian, C. V. Jawahar, R. K. Sarvadevabhatla, and R. Saluja, ‘‘Detecting, tracking and counting motorcycle rider traffic violations on unconstrained roads,’’ in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Workshops (CVPRW), Jun. 2022, pp. 4302–4311
[19] H. Lin, J. D. Deng, D. Albers, and F. W. Siebert, ‘‘Helmet use detection of tracked motorcycles using CNN-based multi-task learning,’’ IEEE Access, vol. 8, pp. 162073–162084, 2020
[20] A. M. Vakani, A. K. Singh, S. Saksena, and H. R. Vanamala, ‘‘Automatic license plate recognition of bikers with no helmets,’’ in Proc. IEEE 17th India Council Int. Conf. (INDICON), Dec. 2020, pp. 1–5
[1]