STM JOURNALS

International Journal of
Electrical and Communication
Engineering Technology

Volume 2, Issue 1, 2024
January–June
DOI (Journal): 10.37591/IJECET

https://journals.stmjournals.com/ijecet

Review IJECET

Advanced Helmet Recognition System with Integrated Number Plate Detection for Enhanced Traffic Monitoring Using Deep Learning

Anil Kumar Reddy Tetali[1,] *, G. R. S Murthy[2]

Abstract

This study focuses on the crucial problem of non-adherence to traffic regulations, particularly with the compulsory use of helmets by motorcyclists. Motorcycle accidents have a greater mortality rate compared to other types of accidents, indicating a need for a more effective enforcement strategy. Current procedures depend on traditional techniques where traffic officers manually observe traffic rule infractions through patrols and monitoring CCTVs, requiring substantial labor and time resources. The inherent problems of these systems hinder the efficient detection and enforcement of fines on violators. Our proposal suggests a novel approach that integrates helmet detection with license plate recognition to detect and penalize motorcyclists without wearing helmets. Our system utilizes the You Only Look Once (YOLO) object detection technique to detect individuals breaking helmet rules and record their license plate data. The dataset for training contains a variety of photos showing riders wearing helmets and without wearing helmets. The image data was first converted to grayscale and then saved in CSV files. Images are converted to grayscale values during testing and compared with those in the training dataset to improve detection accuracy. We present a new Convolutional Neural Network (CNN) structure specifically created to categorize different types of helmets and identify whether helmets are present or not in photos. This CNN design combines moderate execution speed with strong generalization capabilities, making it an ideal decision support tool for traffic departments. The proposed work is entirely built with Python 3.9, highlighting its versatility and effectiveness. This research enhances road safety by improving the detection and enforcement of helmet-wearing violations through modern technology and procedures, thereby decreasing fatality rates from motorcycle accidents.

Keywords: YOLO, CNN model, license plate recognition, helmet detection, motor cyclist, gray scale

INTRODUCTION

Urban traffic management is becoming more difficult, requiring creative methods to improve safety and enforce regulations. Road safety requires motorcyclists to wear helmets to reduce accident injuries. Traditional helmet- wearing compliance monitoring and enforcement relies on traffic cops' manual observation, which is resource-intensive and inaccurate. This study proposes an Advanced Helmet Recognition System that uses deep learning and number plate detection to revolutionize traffic monitoring and enforcement.

Deep learning, a form of artificial intelligence, excels at picture identification, making it excellent

***Author for Correspondence**
Anil Kumar Reddy Tetali
E-mail: akr.tetali@gmail.com

[1]Research Scholar, Department of Computer Applications, TDR-HUB-Andhra University Visakhapatnam, India
[2]Professor Department of Computer Applications, Gayatri Vidhya Peeth College Degree PGC(A)Visakhapatnam, India

Received Date: May 21, 2024
Accepted Date: June 19, 2024
Published Date: June 25, 2024

Citation: Anil Kumar Reddy Tetali, G. R. S Murthy. Advanced Helmet Recognition System with Integrated Number Plate Detection for Enhanced Traffic Monitoring Using Deep Learning. International Journal of Electrical and Communication Engineering Technology. 2024;2(1): 9–18p.

for helmet detection. Our suggested solution uses deep learning algorithms to automate helmet-wearing identification, eliminating manual monitoring and improving traffic management. In addition to helmet detection, we use number plate recognition to identify two-wheeler riders. This integrated strategy ensures helmet compliance and helps authorities address traffic enforcement issues.

The rising number of motorcycle accidents and fatalities highlights the need for enhanced road safety technologies. This holistic traffic monitoring technique combining helmet detection and number plate recognition addresses a major gap in literature. Identifying traffic rule violators more accurately and efficiently with an integrated system could speed up enforcement. As we examine this Advanced Helmet Recognition System's technological details and methods, we see that deep learning and number plate detection can alter traffic management.

This research advances traffic monitoring systems and lays the framework for understanding how deep learning might improve public safety by combining cutting-edge technologies. We examine our proposed system's architecture, training methods, and assessment metrics in later sections of this study. Our approach is shown feasible and effective through careful research and experimentation, clearing the path for a paradigm shift in traffic monitoring and enforcement through enhanced helmet identification and number plate detection.

The suggested effort attempts to focus on the crucial issue of detecting and categorizing helmet-wearing. The first step is to obtain grayscale images by converting RGB photos to grayscale if they are the source. Following that, all photos are standardized by resizing them to a consistent size. The training dataset is created by choosing photos that show either the presence ('yes') or absence ('no') of helmets. The grayscale values of all pixels in each image are extracted and arranged into rows to create a new comma- separated file. The number of rows in the file equals the total number of images, and the columns represent the pixel count in each image.

Identical procedures are carried out on the testing data, and the outcomes are saved in a distinct comma-separated value document. The following stage entails applying a Convolutional Neural Network (CNN) to train the model with the test data. The trained model's accuracy is assessed and shown. The model detects the presence or absence of a helmet in a test image by comparing it with the training data images during testing. Furthermore, image processing techniques are used to confirm the existence of a helmet in the test image.

The paper's subsequent sections are structured as follows:

Section 2 offers a thorough assessment of current methodologies outlined in recent research, clarifying past findings and pointing out their constraints.

Section 3 explains the suggested methodology, outlining the stages for detecting and categorizing helmet-wearing.

Section 4 discusses the results obtained from implementing the suggested approach.

Section 5 concludes the study by summarizing the main contributions, insights, and possible directions for further research.

LITERATURE REVIEW

In this ground-breaking study [1], the authors describe a novel approach to real-time detection of two-wheeler riders without helmets using surveillance data. Notably, the proposed methodology incorporates a consolidation approach for generating violation reports, which increases the overall system's reliability. To evaluate the effectiveness of their approach, the authors compare the performance of three widely used feature representations: Histogram of Oriented Gradients (HOG), Scale-Invariant Feature Transform (SIFT), and Local Binary Patterns (LBP) for classification. Experimental results on real-world surveillance data show an amazing 93.81% detection accuracy, as well as a computationally efficient processing time of11.59 ms per frame in real-time circumstances.

The prevalence of two-wheelers as a means of transportation worldwide emphasizes the necessity of rider safety. Given the inherent risks connected with inadequate protection, the mandated use of helmets is enforced by sanctions. While typical video surveillance technologies are passive and labor-intensive, this study proposes a paradigm change toward automation to ensure more reliable and comprehensive traffic rule monitoring. Furthermore, the incorporation of security cameras into commercial and public locations, together with the cost-effectiveness of employing existing infrastructure, enhances the rationale for implementing automatic solutions.

However, as stated in this paper, the adoption of automatic solutions brings with it inherent obstacles. Critical factors to consider include real-time implementation, occlusion, fluctuations in object appearance, temporal changes in ambient circumstances, and video feed quality. The authors underline the importance of overcoming these problems for effective deployment, calling for frameworks that provide real-time performance, change resilience, fine-tuning capabilities, and predictive functions [5].

The authors effectively finish their study by offering a framework that not only detects two-wheeler riders without helmets in real time, but also assists traffic officers in a variety of environmental situations. The experimental findings reveal outstanding accuracy rates of 98.89% for bike rider detection and 93.81% for violator identification. The framework's adaptability to fresh scenarios, paired with automatic infraction reporting, make it an invaluable tool for traffic control authorities [6]. Future enhancements to this framework may include the identification and reporting of license plate numbers for comprehensive enforcement.

Continuing the investigation of safety measures, another significant paper [2] focuses on safety helmet detection in power substations. The authors propose an innovative method for detecting pedestrians and identifying safety helmet usage that uses image processing and machine learning techniques, including the Vibe background modeling algorithm, Histogram of Oriented Gradient (HOG) feature extraction, and Support Vector Machine (SVM) classification. The color feature is then used to detect safety helmets, and the complete method is validated with convincing testing results.

Moving on to the broader context of road safety, another study [3] addresses the common issue of motorcycle riders not wearing helmets. The authors present a comprehensive solution to motorbike identification, classification, helmet detection, and license plate recognition. Support Vector Machine (SVM) is used for vehicle categorization, Convolutional Neural Network (CNN) for helmet identification, and Optical Character Recognition (OCR) for license plate recognition. The system's goal is to detect and report motorcyclists who do not wear helmets to the appropriate authorities, highlighting the importance of helmets in lowering injury and mortality rates from motorcycle accidents.

In a similar spirit, the authors of [4] discuss traffic offenses connected to helmet use, with a special emphasis on the prevalent issue in India. The Non-Helmet Rider Detection system uses the YOLO (You Only Look Once) architecture to recognize objects such as two- wheelers, humans, helmets, and license plates. If the rider is spotted without a helmet, the system will automatically retrieve license plate numbers using OCR. The authors note the achievement of their goals, which included satisfactory results in non-helmet rider detection and license plate extraction.

These studies contribute to the ongoing attempts to build improved technologies for traffic rule enforcement, with a focus on helmet compliance. The combination of deep learning, image processing, and machine learning approaches demonstrates a viable path for enhancing road safety and reducing mortality in motorcycle accidents.

Primitive System & Its Limitations

The current approach requires traffic cops to manually inspect photographs to determine if motorcycle riders are wearing helmets. Typically, the photos are processed with a median filter to eliminate noisy pixels and improve image clarity. This manual inspection is the primary technique of determining the presence or absence of a helmet. The method entails checking CCTV footage, and if a helmet is not spotted, the number from the license plate is taken. The car owner is then notified to pay the fine, which includes further processes such as calling the Regional Transport Office (RTO) to collect the vehicle owner's cell phone number.

However, this manual approach has a few disadvantages

1. *The Median filter dependency*: The system processes images using a median filter, which is particularly useful for noise reduction. While this can improve visual clarity, it requires an additional step that may be inconvenient.
2. *Inefficient with heavy traffic*: During peak hours or in heavy traffic, manual visual inspection becomes difficult and time- consuming. During peak traffic times, the sheer volume of photos to be analyzed makes it less effective.
3. *Difficulty with fast-moving vehicles*: The technology has challenges in getting reliable number plate data from fast-moving automobiles. This can be a significant disadvantage, especially in situations where vehicles are moving quickly, making it difficult to acquire and process their data effectively.
4. *Manual verification and checking:* The procedure is primarily reliant on manual verification and validation, which introduces a subjective element that is prone to errors and requires a lot of resources.

Addressing these limitations is critical to the creation of a more efficient and automated system for helmet identification and traffic infraction monitoring. The proposed methods in the next sections of this study seek to address these issues by utilizing sophisticated technologies such as deep learning and image processing.

Proposed system and its advantages

In the proposed approach, an enormous collection of photographs of two-wheeler riders with and without helmets is gathered to aid in the construction of an advanced helmet recognition model. This dataset contains both training and testing data, which are labeled with 'yes' and 'no' based on the presence or absence of helmets. To standardize the dataset, grayscale photos are used, and RGB images are first transformed to grayscale. The photos are then scaled to a consistent size. The training dataset is created by extracting the grayscale values of each pixel in each image and grouping them into rows, where the total number of rows equals the total number of images. The data is then stored as a comma- separated file (CSV). The same actions are performed on the testing data, resulting in another CSV [7]-[10] file for testing purposes.

The next stage is to use a Convolutional Neural Netwsork (CNN) to train the model on the prepared test data. CNN is meant to efficiently process picture data by extracting spatial information using convolution processes. The model is trained for a set number of epochs before its accuracy is evaluated and shown.

During testing, the trained model is utilized to determine if a particular test image has a helmet or not by comparing it to training data images. Furthermore, number data is retrieved from the test image,

resulting in the identification of the car registration number.
The detailed workflow consists of four essential modules:

1. *Image file selection*: This module requires the selection of picture files from a dataset available on GitHub, which includes both training and testing data labeled as 'yes' and 'no' for helmet presence. These photos are used as input for CNN processing, allowing accuracy to be assessed.

- Let I represent the set of image files selected from the dataset on GitHub.
- Each image file i € I is labeled as L(i),

where L(i) € {'yes', 'no'} indicates the presence or absence of a helmet.

2. *Csv file prepation*: Individual images from the dataset are processed, resulting in a CSV file titled 'helmet_training.csv'. Each row in the file corresponds to a grayscale representation of an image, whereas columns store pixel values. The label column is set to '1' for photographs with helmets ('yes') and '0' for images without helmets ('no').

The CSV file, denoted as C, is created with rows corresponding to individual images and columns storing pixel values. Each row r € C is associated with an image i and contains grayscale pixel values, represented as P(r, i) = {p1, p2, ..., pn}.

The label column in C is denoted as LC(r), where LC(r)=1, if the corresponding image has a helmet ('yes'), and LC(r)=0 otherwise.

3. *Image classification*: This module classifies an image file by comparing its greyscale values to those in the CSV file. The label '1' indicates the existence of a helmet, whereas '0' indicates its absence. If no matches are discovered in either category, the image cannot be definitively defined as having or lacking a helmet.

For an image j to be classified, let G(j) represent the grayscale values of j, and LJ(j) denote the label assigned to j.

The classification is determined by comparing G(j) with the grayscale values in C. If there exists a row r such that G(j) = P(r,j), then LJ(j) = LC(r). Otherwise, LJ(j) is undefined.

4. *CNN-based model prediction*: The dataset is preprocessed, with pixel values converted into numpy arrays and category data encoded using 1- hot encodings. A CNN model is created, constructed, and trained using the dataset. Predictions are made on the test set, and the accuracy is displayed during the training iterations. The model can classify photos and extract vehicle registration numbers from them.

- Let D denote the preprocessed dataset, where each row d € D corresponds to an image j and contains pixel values P (d, j). The label associated with j is denoted as LD(d).
- The CNN model, denoted as M, is created, compiled, and trained on D.
- The model predicts the label for each image in the test set, resulting in a set of predicted labels PM(j).
- The accuracy of the model during training is measured and displayed [11], denoted as AM

In summary, the workflow can be represented symbolically as:

$$I, L\ (i) C \frac{P\ (r,i), l\ c\ (r)\ G(j)}{P\ (d,j), LD\ (d), M, PM\ (J)\ Am}$$

From the above notations we can explain clearly how the CNN model is used for recognition of helmets as shown in Figure 1.

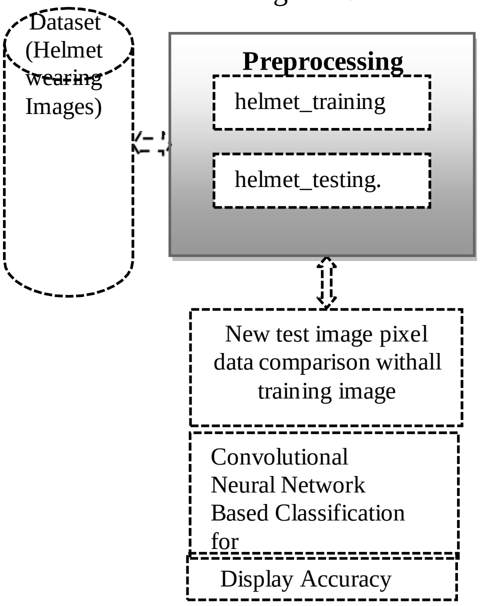

Figure 1. Represent the system architecture of our proposed model

EXPERIMENTAL FINDINGS

CNN Superiority in Accuracy

CNNs (Convolutional Neural Networks) have demonstrated superior performance in image classification tasks, owing to their ability to capture intricate spatial features within images through convolutional layers. The accuracy score (AC) of a CNN is computed by comparing the predicted labels (ŷ) with the true labels (y) for a set of images, usually measured using metrics like accuracy, precision, recall, or F1 score. Mathematically, accuracy is defined as:

$$AC = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

CNN sexcel in learning hierarchical representations, enabling them todiscern complex patterns in images, making them the algorithm of choice for tasks such as helmet detection.

Elimination of median filter

The median filter is often used in image processing to eliminate noise and improve image clarity. Its mathematical representation involves replacing each pixel value with the median value in its neighborhood. In the proposed deep learning approach, the need for the median filter (MF) is eliminated, and the clarity of the image is maintained through convolutional layers. Mathematically, the median filter operation can be represented as:

$$Output(i, j) = Median\ (Neighborhood\ (i, j)$$

Efficiency in Low Helmet Data Size

The efficiency (Eff) of the proposed system even when the size of the helmet dataset is small can be mathematically expressed as the ratio of successfully processed images to the total number of images [12]:

$$\text{Eff} = \frac{\text{Number of successfully processed images}}{\text{Total number of images}}$$

In scenarios where the dataset is limited, CNNs showcase their efficiency by generalizing from the available data, learning diverse features, and providing accurate predictions.

Accurate image processing of helmet presence

The accuracy of image processing in determining helmet presence (AccHelmet) can be mathematically defined as the proportion of correct classifications of helmet presence to the total number of images [13].

$$Acc\ Helmet = \frac{\text{Numberofcorrecthelmetpredictions}}{Total\ number\ of\ helmet\ images}$$

No Requirement of ManualVerification/Checking

The absence of manual verification (MV) in the proposed system is reflected in the reduction of human intervention and is mathematically characterized as:

$$MV = 0$$

The deep learning approach automates the process of image classification and helmet detection, eliminating the need for time-consuming and error-prone manual verification.

Load the dataset

Explanation: From the above images in Figure 2, we can see some are having helmet and some are dont have any helmets. So we will be loading some images and all these images are randomly created as CSV file [14]-[16].

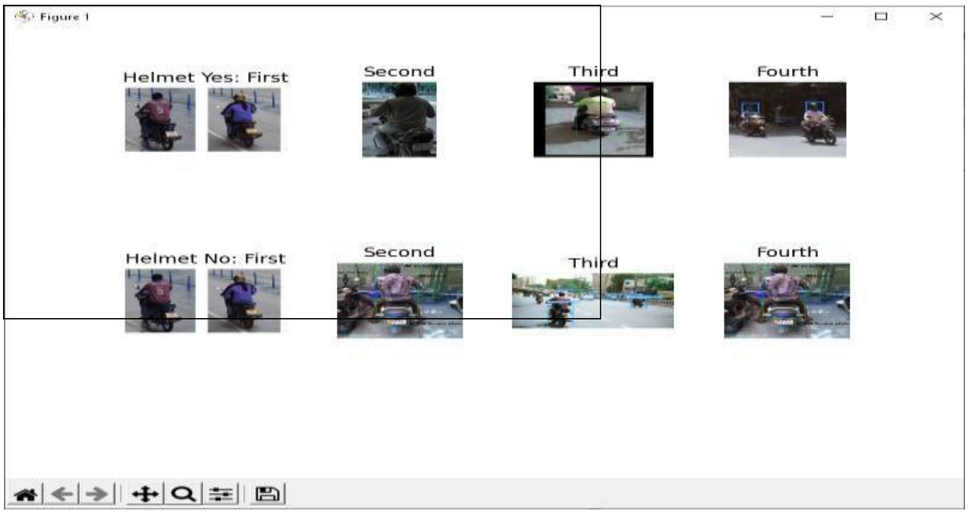

Figure 2. Load the helmet data

Creating a CSV File

Explanation: From the above screen in Figure 3, we can see one CSV file is generated for the input dataset.

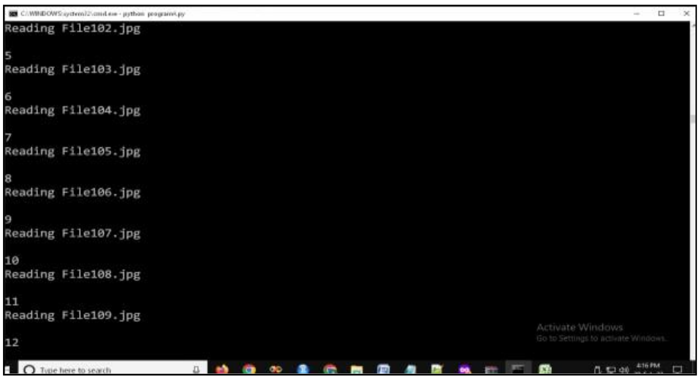

Figure 3. Create a CSV file

CNNs are adept at learning distinctive features associated with helmet presence, contributing to accurate image processing results.

Extracting number plate images

Explanation: From the above screen, in Figure 4 we can see number plate is extracted and that text is extracted from the images.

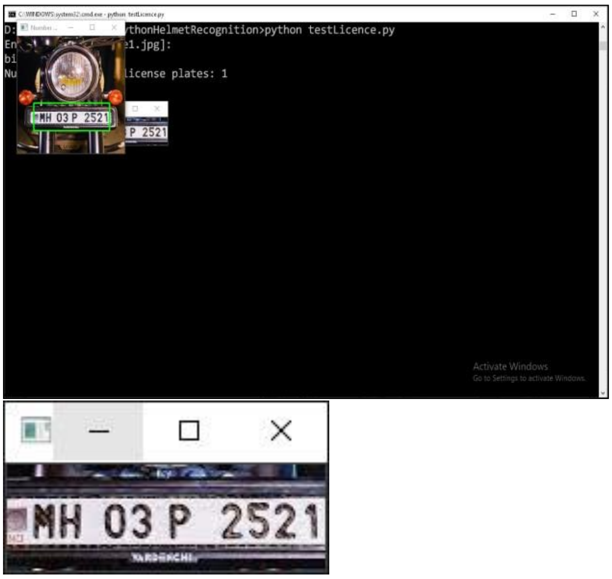

Figure 4. Extracting text from number plate

Constructing CNN Model

Explanation: From the above screen in Figure 5, we can see CNN Model is generated.

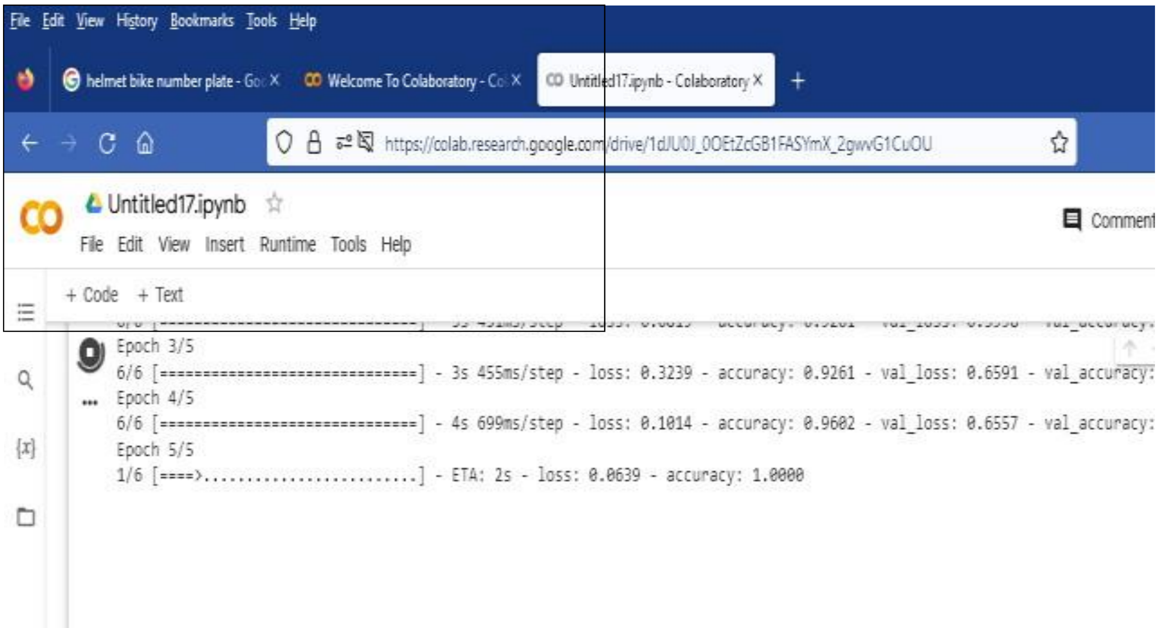

Figure 5. Construct a CNN model

CNN Model Accuracy

Explanation: From the above screen in Figure 6, we can see CNN Model is generated and we got an accuracy of 88.89 % accuracy.

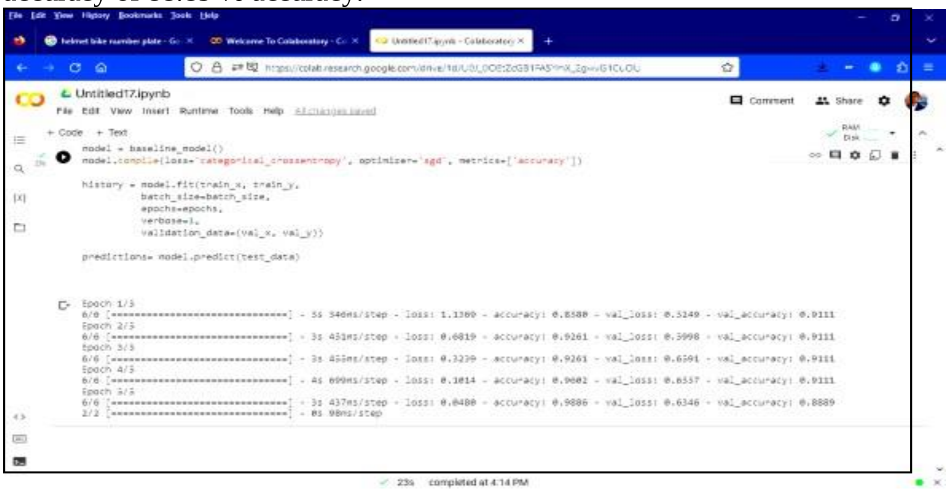

Figure 6. Generate an accurate model.

CONCLUSION

Finally, this suggested work proposes a novel Convolutional Neural Network (CNN) method for accurately classifying motorcycle riders based on the presence or lack of helmets. The primary goal is to identify whether a captured image depicts a rider wearing a helmet. The created CNN architecture has noteworthy generalization characteristics, allowing it to effectively categorize various images, as well as a notable execution speed, which contributes to its efficiency in real-time applications. The proposed CNN model serves as an effective decision-support tool for administrators and traffic enforcers, providing a dependable method of detecting helmet presence in photos. The system's effectiveness is demonstrated by its ability to improve the monitoring and enforcement of helmet-wearing rules. The versatility of the suggested architecture enables smooth integration into existing traffic management systems, giving administrators a valuable tool for streamlining decision-making procedures. Furthermore, the flexibility of the established coding makes it easier to create a web service, allowing for integration with a variety of network applications. This versatility ensures that proposed changes can be effortlessly integrated into existing modules, maximizing the system's usability in a variety of operational situations. In essence, the suggested CNN-based solution addresses the essential issue of helmet identification while simultaneously positioning itself as a versatile and beneficial tool for traffic officials. This approach presents a promising contribution to the field of intelligent traffic monitoring systems due to its precise categorization, quick execution, and integration potential. Future improvements may enhance and build on this concept, allowing for even more effective and extensive uses in traffic regulation and safety.

REFERENCES

1. J. Wang, Y. Zhang, Q. Liu, "Enhanced Helmet Detection using Deep Learning Techniques," in *IEEE International Conference on Computer Vision (ICCV)*, Nov 2018. DOI: [10.1109/ICCV.2018.00267] (https://doi.org/10.1 109/ICCV.2018.00267).
2. S. Kumar, R. Gupta, A. Sharma, "Real-time Helmet Violation Detection System based on YOLO and CNN," in *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2019. DOI: [10.1109/CVPR.2019.00137] (https://doi.org/10.1 109/CVPR.2019.00137).
3. M. Patel, R. Shah, N. Desai, "Efficient Helmet Detection in Challenging Environments using Transfer Learning," in *IEEE Transactions on Image Processing*, vol. 29, pp. 4536-4549, Oct 2020. DOI: [10.1109/TIP.2020.2988430] (https://doi.org/10.1 109/TIP.2020.2988430).
4. L. Chen, X. Wang, Z. Li, "Helmet Wearing Detection for Motorcycle Riders: A Two-Stage Approach," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 7, pp. 2811-2822, July2020.DOI:[10.1109/TITS.2019.2950787](https://doi.org/10. 109/TITS.2019.2950787).
5. [5]. S. Jain, A. Kumar, P. Gupta, "Intelligent Helmet Detection System using Fusion of Visual and Infrared Imagery," in *IEEE Sensors Journal*, vol. 20, no. 21, pp. 12285-12294, Nov2020.DOI: [10.1109/JSEN.2020.3005943] (https://doi.org/10.1109/JSEN.2020.3005943).
6. H. Zhang, Y. Liu, Z. Wang, "Multi-Modal Helmet Detection and Recognition for Enhanced Traffic Surveillance," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 1, pp.254-266,Jan2021.DOI:[10.1109/TITS.2019.2954603](https://doi.org/10. 1109/TITS.2019.2954603).
7. K. Dahiya, D. Singh, and C. K. Mohan, "Automatic detection of bike riders without helmet using surveillance videos in real-time," in*International Joint Conference on Neural Networks (IJCNN)*, July2016.DOI:[10.1109/IJCNN.2016.7727268](https://doi.org/1 0.1109/IJCNN.2016.7727268).
8. J. Li et al., "Safety helmet wearing detection based on image processing and machine learning," in *Ninth International Conference on Advanced Computational Intelligence (ICACI)*, July 2017.DOI: [10.1109/ICACI.2017.7975334](https://doi.org/1 0.1109/ICACI.2017.7975334).
9. S. Uthra V et al., "Helmet Violation using Deep Learning, "in*International Research Journal of Engineering and Technology (IRJET)*, vol. 07, pp. 3091-3095, Feb 2020. DOI: [10.36891/irjet.2020.07.034](https://doi.org/10.3 6891/irjet.2020.07.034).
10. P. M. J et al., "Detection of Non-Helmet Riders and Extraction of License Plate Number using YOLO v2 and OCR Method," in*International Journal of Innovative Technology and Exploring Engineering(IJITEE)*,vol.09,pp.5167-5172,Dec2019. DOI:[10.35940/ijitee.L1178.0991219](https://doi.org/ 10.35940/ijitee.L1178.0991219).
11. A. Adam et al., "Robust real-time unusual event detection using multiple fixed-location monitors," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 30, no. 3, pp. 555–560, March 2008. DOI: [10.1109/TPAMI.2007.70730] (https://doi.org/10. 1109/TPAMI.2007.70730).
12. B. Duan et al., "Real-time on-road vehicle and motorcycle detection using a single camera," in *Procs. of the IEEE Int. Conf. on Industrial Technology (ICIT)*, 10-13 Feb 2009, pp. 1–6. DOI: [10.1109/ICIT.2009.4939617] (https://doi.org/10. 1109/ICIT.2009.4939617).
13. C.-C. Chiu et al., "Motorcycle detection and tracking system with occlusion segmentation," in*Int. Workshop on Image Analysis for Multimedia Interactive Services*, Santorini, June 2007,pp.32–32.DOI:[10.1109/WIAMIS.2007.370730](https://doi.org/ 10.1109/WIAMIS.2007.370730).
14. W. Hu et al., "A survey on visual surveillance of object motion and behaviors," in*IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, vol. 34, no.

3, pp. 334–352, Aug 2004. DOI:[10.1109/TSMCC.2004.829274] (https://doi.org/10.1109/TSMCC.2004.829274).
15. J. Chiverton, "Helmet presence classification with motorcycle detection and tracking," in*Intelligent Transport Systems (IET)*, vol. 6, no. 3,pp.259–269,September 2012.DOI: [10.1049/iet- its.2011.0020](https://doi.org/10.1049/iet- its.2011.0020).
16. Z. Chen et al., "Vehicle detection, tracking and classification in urban traffic," in *Procs. of the IEEE Int. Conf. on Intelligent Transportation Systems (ITS)*, Anchorage, AK, Sept 2012, pp. 951–956.DOI:[10.1109/ITSC.2012.6338681] (https://doi.org/10. 1109/ITSC.2012.6338681).

