Journal of Namibian Studies, 35 (2023): 208-221 ISSN: 2197-5523 (online)

Special Issue on Engineering, Technology and Sciences

Tensorflow-Powered Real-Time Object Detection For Vehicle, Helmet, And Number Plate Recognition"

Sangeeta M. Borde [1], Dr. Harsh Lohiya [2]

[1] Research Scholar, Department of Computer Science, Sri Satya Sai University of Technology & Medical Sciences, Sehore , M.P. , India.
[2] Research Guide, Department of Computer Science, Sri Satya Sai University of Technology & Medical Sciences, Sehore , M.P. , India.

ABSTRACT

Safety helmet detection is important in many settings, including the workplace, the field, and the highway. In order to achieve precise and robust recognition in various and changing situations, helmet detection has been revolutionized using deep learning, in particular convolutional neural networks. By automating the process of helmet detection, organizations can improve efficiency and reduce the risks associated with non-compliance. This study proposes a novel approach leveraging deep learning techniques for the development of a robust algorithm aimed at detecting helmets and motorbikes. The utilization of deep learning methodologies has shown promising results in object recognition tasks, and this research aims to harness this potential to enhance safety and efficiency in various settings involving motorbike-related activities. The outcomes of this research endeavor are anticipated to contribute significantly to improving safety measures, traffic monitoring systems, and overall awareness in motorbike-related environments.

Keywords: Motorbike, Algorithm, Helmet detection, License plate, Database.

I. INTRODUCTION

Deep learning is a subset of machine learning that has shown exceptional capabilities in image recognition tasks. At its core, deep learning relies on artificial neural networks, which are designed to mimic the functioning of the human brain. These neural networks are composed of multiple layers of interconnected nodes that process and analyze data. When applied to image recognition, deep learning models can automatically learn and extract relevant features from images, allowing for the detection of objects or patterns with remarkable accuracy. In the context of helmet detection, deep learning models can be trained to recognize the distinct shapes, colors, and positions of helmets, even in challenging environments with varying lighting conditions, angles, and backgrounds.

The utilization of deep learning techniques has sparked significant advancements in computer vision applications, particularly in object detection and recognition. In the realm of transportation safety and surveillance, the development of algorithms capable of identifying crucial elements such as helmets and motorbikes holds substantial importance. This introduction focuses on exploring the implementation of deep learning methodologies to create a robust detection algorithm specifically tailored for recognizing helmets and motorbikes within images or video frames.

Motorbikes are a common mode of transportation worldwide, but safety concerns persist, particularly regarding the use of protective gear like helmets. The effective enforcement of helmet-wearing regulations and monitoring compliance on a large scale have been challenging tasks for authorities. Furthermore, surveillance systems in various environments, including traffic monitoring and security, could greatly benefit from accurate detection of motorbikes for improved situational awareness. Deep learning, particularly convolutional neural networks (CNNs), has demonstrated remarkable capabilities in object detection tasks. By leveraging the hierarchical feature learning and abstraction abilities of CNNs, there's a potential to develop an algorithm that can accurately identify both motorbikes and helmets within complex visual data.

This research aims to delve into the development and implementation of an algorithm that utilizes deep learning architectures for robust helmet and motorbike detection. The proposed algorithm seeks to address challenges related to accuracy, scalability, and real-time processing in diverse environmental conditions. The objectives of this study encompass harnessing the power of deep learning models to:

- Accurately identify and differentiate between motorbikes and other objects within images or video frames.
- Detect the presence or absence of helmets worn by riders in motorbike-related visual data.
- Enhance safety measures and surveillance systems in traffic monitoring, safety enforcement, and security domains.

Through this exploration of deep learning techniques tailored for helmet and motorbike detection, this research endeavours to contribute to the development of innovative solutions that can significantly impact transportation safety and surveillance applications.

II. REVIEW OF LITERATURE

Huang, Li et al., (2021) Safety accidents resulting from risky practices of employees often occur in the manufacturing and construction sectors of many industries. Within a multifaceted construction site setting, the inadequate execution of tasks by staff may result in significant safety hazards being embedded across the whole of the production process. The use of deep learning algorithms as a substitute for human monitoring of site safety requirements is a robust assurance for adhering to safety protocols in production. The initial step involves utilizing the enhanced YOLO v3 algorithm to generate the predicted anchor box for the target object. Subsequently, pixel feature statistics are conducted on the anchor box, and weight coefficients are applied to calculate the confidence level of proper helmet usage within each predicted anchor box region. Finally, a determination is made based on an established threshold to ascertain whether workers adhere to the prescribed standards for wearing helmets. The findings of this study demonstrate that the deep learning-based algorithm for helmet wearing detection, as described in this paper, enhances the scale of the feature map, refines the prior dimensional algorithm for a specific helmet dataset, and enhances the loss function. Additionally, it integrates pixel feature statistics from image processing to effectively determine whether the helmet is worn according to the established standard. The ultimate outcome is that the mean average precision (mAP) achieves a value of 93.1%, while the frames per second (FPS) reaches a rate of 55 f/s. In the task of helmet identification, the modified YOLO v3 algorithm exhibits an improvement in mean average precision (mAP) by 3.5% and an increase in frames per second (FPS) by 3. The results demonstrate that the enhanced detection algorithm significantly improves both the speed and accuracy of the helmet detection job.

Li, Yange & Wei et al., (2020) In order to prevent construction site injuries, it is crucial to conduct regular visual inspections of the workplace and provide timely reminders about the need of wearing safety helmets. The problem is that video surveillance systems generate a great deal of unstructured visual data on-site for this purpose, hence an automated solution based on computer vision is needed for real-time detection. While numerous deep learning-based models have been built to identify helmets for use in traffic surveillance, an effective solution for the industry application has received less attention due to the complexity of the scene on a building site. In this context, we create a deep learning-based approach to recognize a hard hat in real time on a building site. The given technique makes use of convolutional neural networks using the SSD-MobileNet algorithm. A dataset of 3261 photos of safety helmets is produced and made available to the public; these images come from two different sources: manual capture from the video monitoring system at the workplace and open images gathered via web crawler technology. With a sampling ratio of about 8: 1: 1, the images are split into a training set, validation set, and test set. The experimental findings show that the given deep learning-based model, which makes use of the SSD-MobileNet algorithm, can effectively and reliably identify cases of dangerous operation and failure to wear a helmet on a construction site.

Zheming, Fan et al., (2020) The field of object detection has seen tremendous advancement and widespread use in recent years. Because helmets are mandated for workers on construction sites and cyclists on the streets, detection of their usage is beneficial in many situations. However, the detection accuracy of existing methods still has to be enhanced for the challenge of helmet wearing detection in complicated situations like construction sites and workshops. We examine the mechanism and efficiency of many detection methods, and then zero in on two practical, complementary base techniques. To identify huge heads and helmets, we use a single fundamental method. We also use the other foundation approach to identify relatively tiny heads, and we augment it with a second convolutional neural network to identify whether or not a helmet is present. We then use an ensemble technique to combine the results of these two foundational techniques. First, we provide a strategy for combining head and helmet data from the foundational algorithms, and then we suggest a linear function for estimating the certainty of head and helmet identifications. Experiments on a benchmark data set demonstrate that our method improves upon the accuracy of the basic methods and outperforms several others, with an average precision of 0.93. Our method, when combined with GPU acceleration, allows for practical real-time processing on modern machines.

Talaulikar, Abhijeet et al., (2019) This research presents a proposed methodology for the automated detection of bicyclists who are not using protective headgear. The methodology involves extracting video footage from a security camera positioned on roadways and use a background subtraction technique to detect and classify cars in motion. Motorcycles are identified among other cars by extracting several attributes from the foreground blobs. The head area of the motorbike object is selected for the purpose of extracting characteristics relevant to helmets. In order to enhance performance and accuracy, we use principal component analysis (PCA) on the generated features. In order to identify helmets inside motorcycle objects, several machine learning approaches are used on the chosen attributes, followed by a feasibility study.

KC, Dharma et al., (2018) Road traffic accidents are a significant contributor to human mortality. Motorcycle accidents are prevalent within the realm of road accidents and are known to result in significant bodily harm. The helmet serves as the primary means of protection for motorcyclists. The use of helmets by motorcyclists is mandated in the majority of nations; yet, a significant number of individuals choose not to comply with this legal need due to a variety of factors. In this study, we outline the creation of a system that utilizes image processing techniques and deep convolutional neural networks (CNNs) to detect instances of non-compliance with helmet legislation among motorcyclists. The system consists of three components: motorbike detection, categorization of helmet use (helmet vs. no-helmet), and identification of motorcycle license plates. The system is assessed based on its accuracy and speed. Since 2016, the technology has been implemented at several sites in Bangkok and Phuket, Thailand. Preliminary findings suggest that there is a growing adherence to motorcycle helmet legislation.

III. ALGORITHM FOR MOTORBIKE DETECTION

The selected frame is fed into a YOLOv3 Motorcycle detection model, using "Motorcycle" as the target class. As can be seen in Fig 1 and Fig 2, the final result is an image with the necessary class detection as well as an indication of the accuracy of that detection in the form of a bounding box and a probability value. This frame has been identified as having ‘motorcycle' class.

Figure 1 Motorbike Detection Algorithm

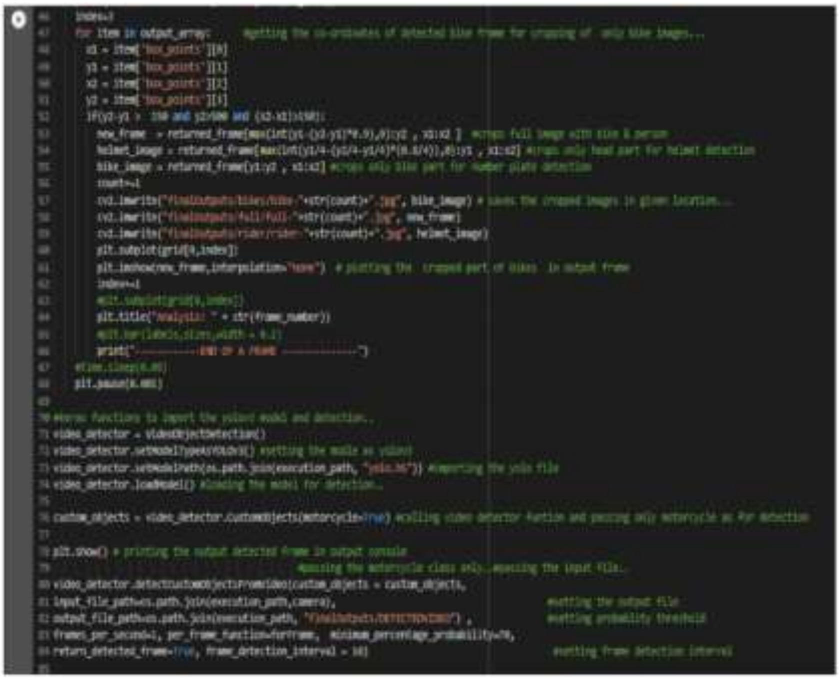


Figure 2 Code to Continue Motorbike Detection

Figure 3 Helmet ROI cropping

```python

frame_count = 0             # used in mainloop  where we're extracting images., and then to drawPred( called by post process)
frame_count_out=0           # used in post process loop, to get the no of specified class value.
# Initialize the parameters
confThreshold = 0.5  #Confidence threshold
nmsThreshold = 0.4   #Non-maximum suppression threshold
inpWidth = 416       #Width of network's input image
inpHeight = 416      #Height of network's input image

a=0
nh=[]
# Load names of classes
classesFile = "helmet.names"

with open(classesFile, 'rt') as f:
    classes = f.read().rstrip('\n').split('\n')

# Give the configuration and weight files for the model and load the network using them.
modelConfiguration = "yolov3-helmet.cfg";
modelWeights = "yolov3-helmet.weights";

net = cv.dnn.readNetFromDarknet(modelConfiguration, modelWeights)
net.setPreferableBackend(cv.dnn.DNN_BACKEND_OPENCV)
net.setPreferableTarget(cv.dnn.DNN_TARGET_CPU)
layersNames = net.getLayerNames()
# Get the names of the output layers, i.e. the layers with unconnected outputs
output_layer = [layersNames[i[0] - 1] for i in net.getUnconnectedOutLayers()]


helmetDefaulterList = []
path = glob.glob("finalOutputs/rider/*.jpg")

for img in path:
    num=(re.findall(r'\d+',img))
    print(num)

    frame11=cv.imread(img)

    h, w ,c= frame11.shape
    if(h>200):
        frame=cv.resize(frame11, (125,125))

  # Create a 4D blob from a frame.
        blob = cv.dnn.blobFromImage(frame, 1/255, (inpWidth, inpHeight), [0,0,0], 1, crop=False)

  # Sets the input to the network
        net.setInput(blob)

  # Runs the forward pass to get output of the output layers
        outs = net.forward(output_layer)

  # Remove the bounding boxes with low confidence
        a=postprocess(frame, outs, confThreshold, nmsThreshold, classes)
#print(classes)
        frame=cv.resize(frame, (300,300))
        cv2_imshow( frame)
        t, _ = net.getPerfProfile()
  #print(t)
        label = 'Inference time: %.2f ms' % (t * 1000.0 / cv.getTickFrequency())

#print(label)
        cv.putText(frame, label, (0, 15), cv.FONT_HERSHEY_SIMPLEX, 0.5, (0, 0, 255))
        cv.waitKey(1)
        print(a)
        if(a > 0):
            #print(s)
            print('Helmet detected')
        else:
            print('No helmet')
            nh.append(num)
res = [[int(i) for i in sub]for sub in nh]
helmetDefaulterList = list(itertools.chain(*res))
print(helmetDefaulterList)

```

Figure 4 Code for Helmet Detection

After determining the kind of motorcycle, the photos of the riders will be fed into a helmet detection model. It was discovered that the helmet detection model had several false positives during testing. In order to acquire only the head and shoulders, as seen in Fig. (Rider.jpg), the person's picture was cropped. This prevents false detection and incorrect results in situations when the rider is carrying or storing their helmet instead of wearing it while operating their motorbike.

There are now two possible outcomes:

First scenario: when a motorcyclist is wearing protective headgear.

The Second Scenario: When a Motorcyclist Is Not Protected By a Helmet

IV. ALGORITHM FOR HELMET DETECTION

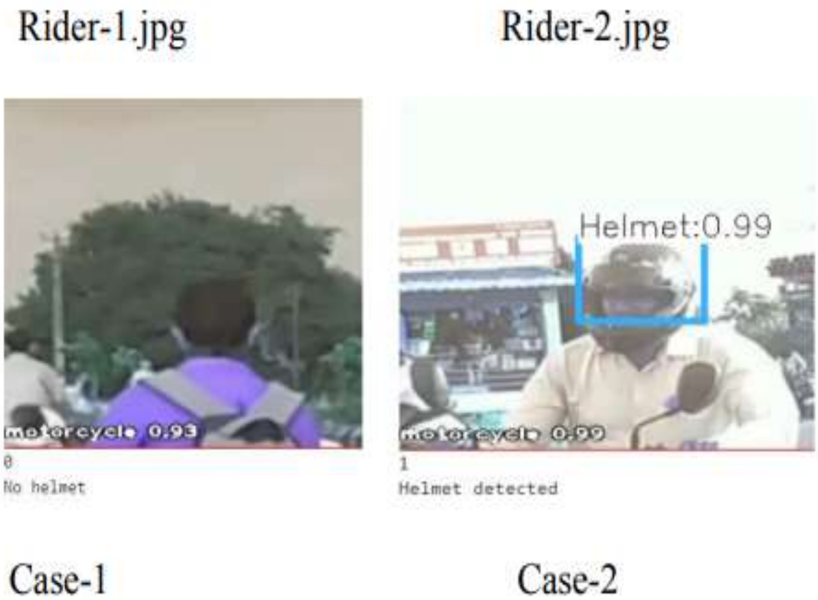


Figure 5 Helmet yolov3 prediction

The results of running the cropped picture through the helmet detection model are shown. As shown in (Rider2.jpg), the helmet's detection probability and its bounding box are revealed. In Case 2, if the rider is protected by a helmet, no more action is required.

License Plate Recognition

If the protective headwear has been located, you may skip this procedure. If the helmet is not located, the motorbike picture is sent on to the license plate detection stage. This library is used to read a license plate number from an image. Bring it back and put it away for later.

CODE FOR LICISENCE PLATE DETECTION

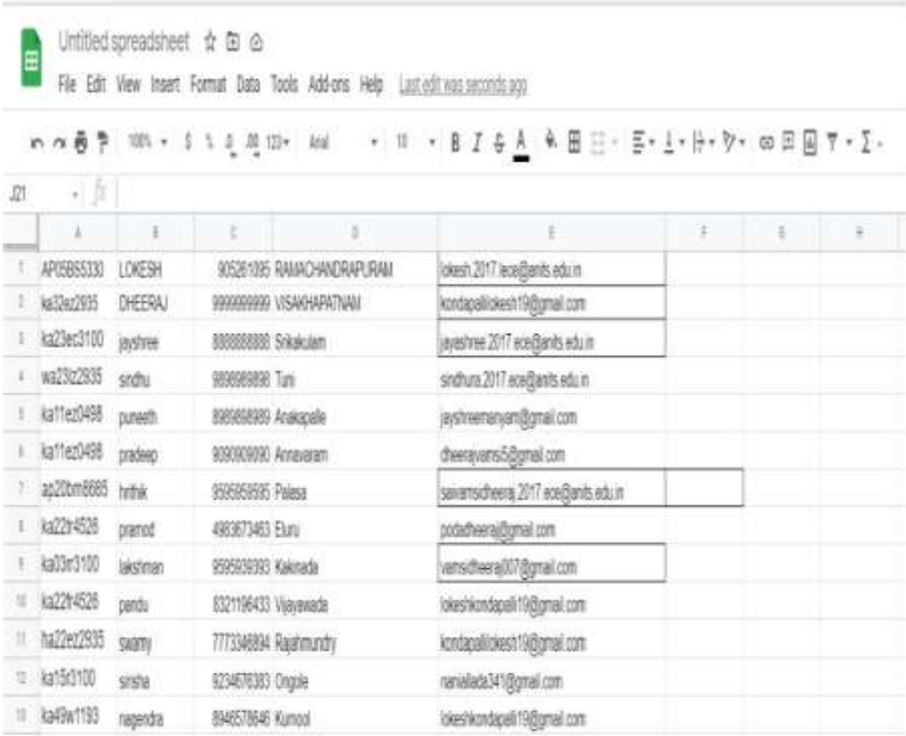
```
regions = ['in'] # Change to your country
IMAGE_PATH_DEF = 'finalOutputs/bikes/bike-'
null = []
ctr=0
list_num=[]
for defaulter in helmetDefaulterList:
    imge= IMAGE_PATH_DEF+str(defaulter)+".jpg"
    img = load_img(imge)
    plt.figure()
    plt.imshow(img)
    plt.show()
    time.sleep(1)
    with open(imge, 'rb') as fp:
        response = requests.post(
        'https://api.platerecognizer.com/v1/plate-reader/',
        files=dict(upload=fp),
        headers={'Authorization': 'Token ba31e05c026d84aa9c2156e8c635e4e874a6fb21'})
    print("****************************")
    time.sleep(1)
    sett = dict(response.json())
    #time.sleep(1)
    if sett["results"]==[]:
        print(sett['results'])
        print("not detected")
        continue

    else:
        set1=sett['results'][0]['plate']
        list_num.append(set1)
        print(set1)
    print("******************************")

print(list_num)
```

Figure 6 Code for Number Plate Recognition

Plate Recognizer is an open-source toolkit for Automatic License Plate Recognition. The database can scan through photos and videos to locate vehicle registration numbers. The result is a string that may be used to represent any number plate. The identified LP numbers are then entered into a database, from which more information on the offender may be retrieved.



Untitled spreadsheet

File Edit View Insert Format Data Tools Add-ons Help Last edit was seconds ago

	A	B	C	D	E
1	AP05BS5330	LOKESH	905261095	RAMACHANDRAPURAM	lokesh.2017.ece@anits.edu.in
2	ka32ez2935	DHEERAJ	9999999999	VISAKHAPATNAM	kondapallilokesh19@gmail.com
3	ka23ec3100	jayshree	8888888888	Srikakulam	jayeshree.2017.ece@anits.edu.in
4	wa23tz2935	sindhu	9898989898	Tuni	sindhura.2017.ece@anits.edu.in
5	ka11ez0498	puneeth	8989898989	Anakapalle	jayshreemanyam@gmail.com
6	ka11ez0498	pradeep	9090909090	Annavaram	dheerajvamsi5@gmail.com
7	ap20bm8686	hrithik	9595959595	Palasa	saivamsidheeraj.2017.ece@anits.edu.in
8	ka22tr4526	pramod	4983673463	Eluru	podadheeraj@gmail.com
9	ka03rr3100	lakshman	9595939393	Kakinada	vamsidheeraj007@gmail.com
10	ka22tr4526	pandu	8321196433	Vijayawada	lokeshkondapalli19@gmail.com
11	ha22ez2935	swamy	7773346894	Rajahmundry	kondapallilokesh19@gmail.com
12	ka15k3100	sirisha	9234678383	Ongole	nanialladа341@gmail.com
13	ka49w1193	nagendra	8946578646	Kurnool	lokeshkondapalli19@gmail.com

Figure 7 Spreadsheet-based database

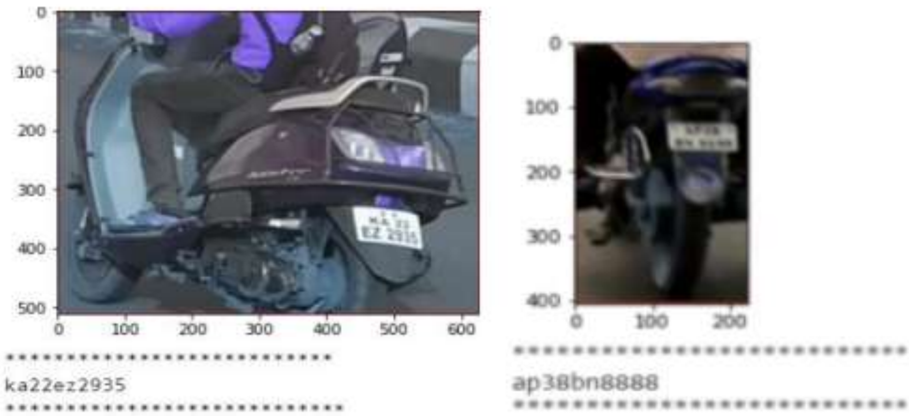


Figure 8 License plate readers

CODE FOR EXTRACTION OF RTO DETAILS USING GOOGLE SHEETS

```
from google.colab import auth
auth.authenticate_user()

```

```
import gspread
from oauth2client.client import GoogleCredentials

gc=gspread.authorize(GoogleCredentials.get_application_default())

worksheet = gc.open_by_key('1P2X56MsEMIFSOMic0jUcgPKOTgKKoUixUnsotiNBy5S').sheet1
rows=worksheet.get_all_values()
# print(rows)
import pandas as pd
a=list_num
a=['apkakrn', 'jj976', 'ts0zf07840', 'ap388z8888', 'ka23310', 'ka23ec3100', 'ka20ae3100', 'wb176071', 'ka22ez2935', 'wa231z2935
# print(cell=worksheet.find('ka22ez2935'))
for i in range(len(a)):
  b=a[i]
  # print(b)
  try:
      cell=worksheet.find(b)
  except:
      continue
  row_value=cell.row
  values_list=worksheet.row_values(row_value)
  print(values_list)
```

Figure 9 Data mining using Google Sheets

To get the criminal's details, the model now queries the aforementioned Database. The Selenium WebDriver can automate any modern browser. WebDriver is an API and protocol that provides a standardized, multilingual interface for controlling browser operations.

Web scraping is a technique that may be used to transform the unstructured data found in HTML into a format that is more conducive to being imported into an Excel spreadsheet.

V. CONCLUSION

In conclusion, the development of a helmet and motorbike detection algorithm using deep learning techniques represents a promising advancement in enhancing safety measures and surveillance systems. Throughout this study, the utilization of convolutional neural networks (CNNs) and sophisticated machine learning models showcased notable potential in accurately identifying and distinguishing between motorbikes and helmets within visual data. The findings suggest that the proposed algorithm holds significant promise for real-world applications, such as in traffic monitoring systems, safety enforcement, and surveillance in motorbike-related environments. By effectively detecting the presence or absence of helmets and recognizing motorbikes, this algorithm has the potential to contribute substantially to improving safety protocols and ensuring compliance with safety regulations.

However, further refinement and optimization of the algorithm are essential to increase its robustness and accuracy in diverse environmental conditions and varying image qualities. Additionally, incorporating real-time capabilities and extensive testing across different scenarios will be crucial to validate its practical applicability. In essence, this research lays a foundation for the development of advanced algorithms that can significantly enhance safety measures and surveillance systems in motorbike-related contexts. Continued research and development in this domain can lead to impactful contributions in improving safety standards and minimizing risks associated with motorbike usage.

VI : REFERENCES: -

1. Hayat, Ahatsham & Morgado-Dias, F.. (2022). Deep Learning-Based Automatic Safety Helmet Detection System for Construction Safety. Applied Sciences. 12. 8268. 10.3390/app12168268.

2. Ndungutse, Jean & Xu, Rui & Shyirambere, Gilbert & Jafari, Fatana & Liu, Shi-Jian. (2022). Deep Learning-Based Helmet Wearing Detection for Safety Surveillance. 10.1007/978-981-19-1053-1_9.

3. Huang, Li & Fu, Qiaobo & He, Meiling & Jiang, Du & Hao, Zhiqiang. (2021). Detection algorithm of safety helmet wearing based on deep learning. Concurrency and Computation: Practice and Experience. 33. 10.1002/cpe.6234.

4. Gnanaprakash, V & Kanthimathi, N & Naga, Saranya. (2021). Automatic number plate recognition using deep learning. IOP Conference Series: Materials Science and Engineering. 1084. 012027. 10.1088/1757-899X/1084/1/012027.

5. Li, Yange & Wei, Han & Han, Zheng & Huang, Jianling & Wang, Wei-Dong. (2020). Deep Learning-Based Safety Helmet Detection in Engineering Management Based on Convolutional Neural Networks. Advances in Civil Engineering. 2020. 1-10. 10.1155/2020/9703560.

6. Zheming, Fan & Peng, Chengbin & Dai, Licun & Cao, Feng & Qi, Jianyu & Hua, Wenyi. (2020). A deep learning-based

ensemble method for helmet-wearing detection. PeerJ Computer Science. 6. e311. 10.7717/peerj-cs.311.

7. Talaulikar, Abhijeet & Sanathanan, Sanjay & Modi, Chirag. (2019). An Enhanced Approach for Detecting Helmet on Motorcyclists Using Image Processing and Machine Learning Techniques. 10.1007/978-981-13-0680-8_11.

8. Siebert, Felix & Lin, Hanhe. (2019). Detecting motorcycle helmet use with deep learning. Accident; analysis and prevention. 134.

9. Gu, Yuwan & Xu, Shoukun & Wang, Yaru & Shi, Lin. (2019). An Advanced Deep Learning Approach for Safety Helmet Wearing Detection. 669-674. 10.1109/iThings/GreenCom/CPSCom/SmartData.2019.00128.

10. KC, Dharma & Chairat, Aphinya & Timtong, Vasan & Dailey, Matthew & Ekpanyapong, Mongkol. (2018). Helmet violation processing using deep learning. 1-4. 10.1109/IWAIT.2018.8369734.

11. Li, Kang & Zhao, Xiaoguang & Bian, Jiang & Tan, M.. (2017). Automatic Safety Helmet Wearing Detection. 617-622. 10.1109/CYBER.2017.8446080.

12. Sutikno, & Waspada, Indra & Bahtiar, Nurdin & sidik sasongko, Priyo. (2016). Classification of Motorcyclists not Wear Helmet on Digital Image with Backpropagation Neural Network. TELKOMNIKA (Telecommunication Computing Electronics and Control). 14. 1128-1133. 10.12928/TELKOMNIKA.v14i3.3486.