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AUTOMATED HELMET DETECTOR FOR RIDER'S WITHOUT HELMET BASED ON DEEP LEARNING

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ABSTRACT

The continued motorization of traffic has resulted in a steady rise in the number of road fatalities and injuries around the world. To combat this, governments are emphasising the importance of enforcing safe and lawful traffic behaviour. There is a paucity of comprehensive data on the safety-critical behavioural metric of motorcycle helmet use, particularly in developing nations where motorcycles are the primary mode of transportation. Due to a lack of data, focused enforcement and education initiatives, which are critical for injury prevention, are not possible. As a result, we used a deep learning approach to construct an algorithm for the automated registration of motorcycle helmet wear from video data. We trained our algorithm to recognise active motorcycles, the number and position of riders on the motorcycle, as well as their helmet use, using 91,000 annotated frames of video footage collected at several observation sites around Myanmar. An investigation of the algorithm's accuracy on an annotated test data set, as well as a comparison to human-registered helmet use data, demonstrates that our approach is extremely accurate. In comparison to a human observer, our algorithm registers motorcycle helmet use rates with an accuracy of -4.4 percent and +2.1 percent, with minimal training for individual observation sites. The accuracy of helmet use detection reduces somewhat without observation site specific training. The proposed method's implications, as well as strategies that can improve detection accuracy, are examined. In the suggested method, bike riders are first identified using the SSD-Mobile Net model, which is a stable version of the cutting-edge object identification methodology SSD-Mobile Net model. A territorial-based Convolutional Neural Network (RCNN)-based engineering has been proposed for bike riders' head protector finding in the next stage.

1. INTRODUCTION

1.1 DEEP LEARNING

Deep learning techniques are aimed at obtaining highlight orders from more significant tiers of the progressive system, which are modified by the production of lower level parts. Without relying only on human-created highlights, a framework can learn sophisticated capacities planning the contribution to the outcome straight forwardly from information by naturally learning highlights at various levels of reflection. Profound learning computations seek to use the obfuscated structure of information flow to uncover great representations, which are frequently at several levels, with higher-level learnt items classified as far as lower-level elements. The PC may learn complicated notions by creating them out of simpler ones thanks to the progressive system of ideas. If we design a diagram to explain how these ideas build on top of one another, the result is a complex chart with several layers. As a result, we refer to this approach to AI as profound learning.

On issue spaces where the sources of information (and, surprise, yield) are simple, profound learning reigns supreme. They are pictures of pixel information, reports of text information, or documents of sound information, rather than a couple of numbers in a simple arrangement.

Deep-learning architectures such as deep neural networks, networks, deep reinforcement learning, recurrent neural networks, and convolutional neural networks have been used in fields such as computer vision, speech recognition, natural language processing, machine translation, bio informatics, drug design, medical image analysis, climate science, material inspection, and board game programmes, where they have produced results that are comparable to, and in some cases surpass, human performance.

1.2 PROPOSED SYSTEM

We promote a deep learning-based technique for the continual discovery of a street-based wellbeing protective cap. The proposed technique makes use of the SSD-Mobile Net computation, which is based on convolutional neural networks. A dataset of 3261 images of security head coverings is laid out and distributed to the general public. The images were taken from two sources: manual capture from the video checking system at the workplace and open images acquired using web crawler technology. The image set is divided into three sections: preparation, approval, and testing, with an examining ratio of around 8:1:1.The findings reveal that the introduced deep learning-based model applying the

SSD-Mobile Net computation is capable of accurately and effectively identifying the risky action of disappointment of wearing a cap at the construction site.

1.2.1 ALGORITHM

Region Based Convolutional Neural Networks

- Locales with convolutional neural organisations (RCNN) are a deep learning strategy that combines rectangular district suggestions with convolutional neural organisation highlights.
- For tracking things from a drone-mounted camera, identifying text in an image, and allowing object detection in Google Lens, researchers deployed Region Based Convolution Neural Network.
- Mask R-CNN is one of seven tasks in the MLPerf Training Benchmark, which is a competition to improve neural network training speed.
- Instead of dealing with a large number of areas, the RCNN computation suggests a large number of boxes in the image and verifies whether any of these crates include at any time.
- For each region proposal, CNN creates a fixed-length feature matrix.
- Using category-specific linear SVM, these features are used to classify region suggestions.
- Bounding box regression is used to refine the bounding boxes so that the object is correctly captured by the box.

ADVANTAGES:

- As a result, it recognises the important elements with minimal human intervention.
- For example, given a large number of photos of felines and canines, it learns certain elements for each class without the help of anybody else. CNN is also computationally efficient, with a precision rate of above 95%.
- Detects significant traits without the need for human intervention.

1.3 SYSTEM ARCHITECTURE

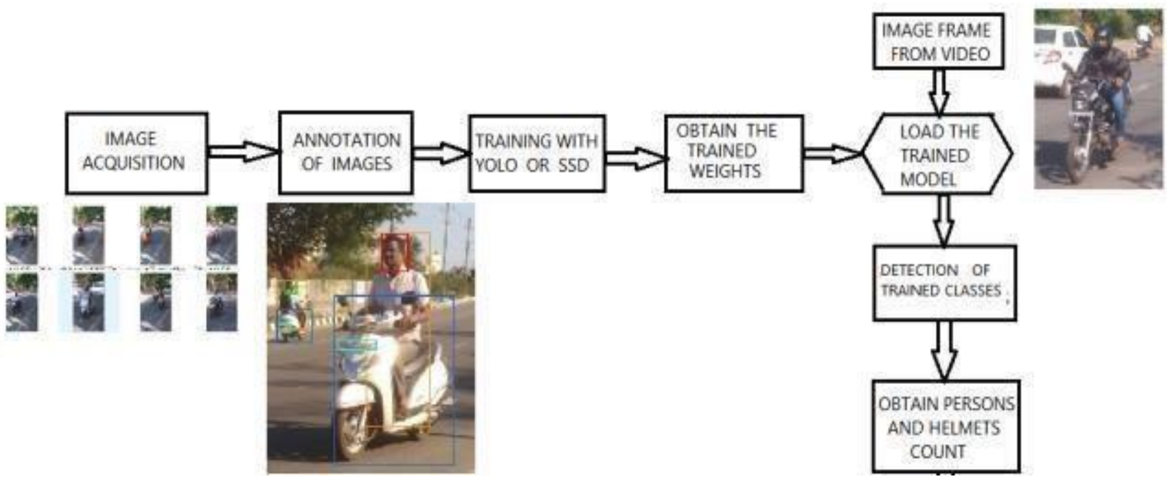


Figure 1 System Architecture

1.4 MODULES

1.4.1 LIST OF MODULES

1. Dataset for Training
2. Open CV and Open Camera
3. Load the Model
4. Identify the Helmet or not

1.4.2 MODULE DESCRIPTION

1. Dataset for Training

- The dataset is used to train the model using Tensorflow and Keras (with and without Helmet)
- We use two types of datasets: traffic surveillance films and picture datasets, each including 3261 images for motorcycle and helmet. With a sampling ratio of about 8:1:1, the image dataset is separated into a training set, validation set, and test set.

2. Open CV and Open Camera

- People are captured and monitored using an open camera, and the open cv detects the faces of those in the frame.
- OpenCV offers a number of pre-trained classifications for identifying items like faces, helmets, and motorcycles. Any of these classifiers can be used to detect the object as needed.

3. Load the Model

- Then we develop a web page to direct the pre-trained model video to detect persons wearing helmets or not.
- We can analyse the videos in the background utilising Anaconda prompt programme.

4. Distinguish the wearing of Helmet or not

- Using a pre-trained model and video analysis, identify the individual wearing a helmet with or without a helmet over a live video feed using a camera
- If the individual is wearing a helmet, the bounding box will be green. If the person is not wearing a helmet, the bounding box will be red.

5. Accuracy for with or without Helmet

- After identifying the helmet, the boundary box accuracy will be projected.
- After identifying the helmet, the boundary box accuracy will be projected.
- The accuracy prediction will be generated by comparing the testing data with pre-trained data.

1.5 PREDICT THE RESULT

Following the investigation of the comments, this module assists in presenting the best results to the client.

1.6 IMPLEMENTATION

The task's execution phase is when the hypothetical plan is translated into a working structure. As a result, it might be considered the first and most important step in creating a successful new framework and assuring the client that the new framework would operate. The execution stage entails careful planning, a review of the current framework and its restrictions on execution, the development of changeover strategies, and the evaluation of changeover approaches. Individuals from numerous divisions and framework examination are present at the time of execution of any framework. They have been confirmed to be capable of supervising various activities of individuals outside of their own data processing offices.

2. RESULT SCREENSHOTS

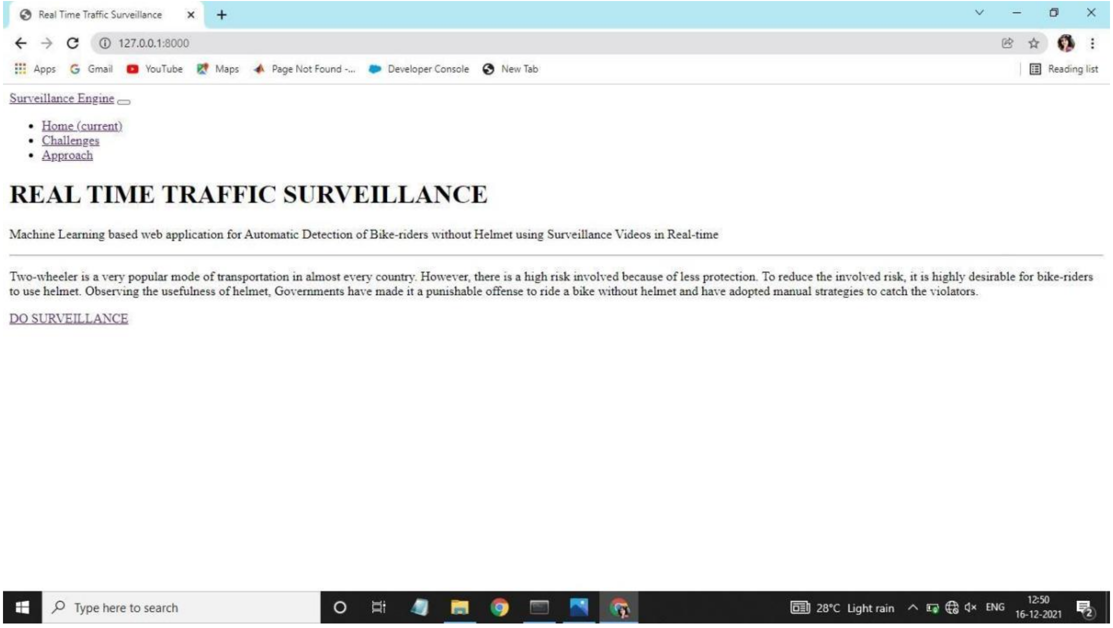


Figure 2 Result Module 1

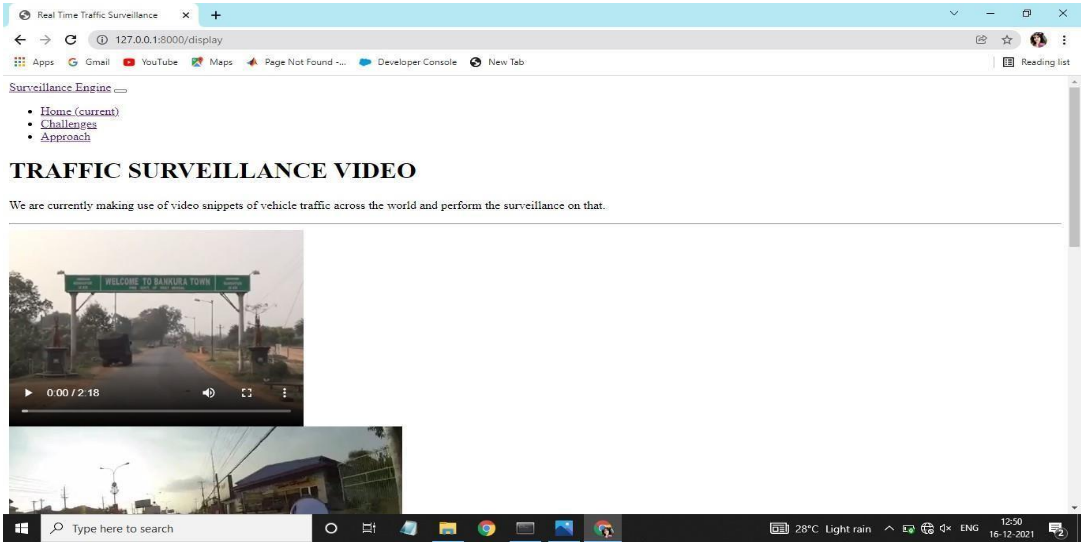


Figure 2 Result Module 2

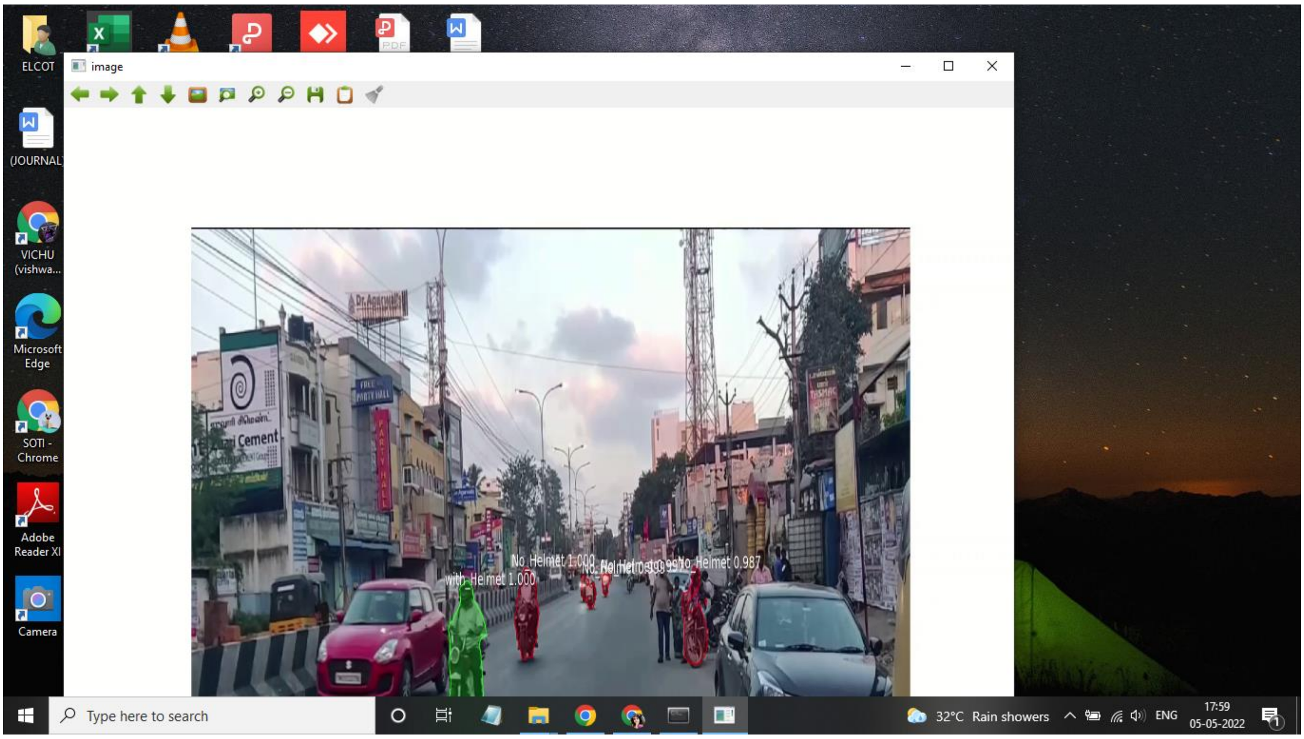
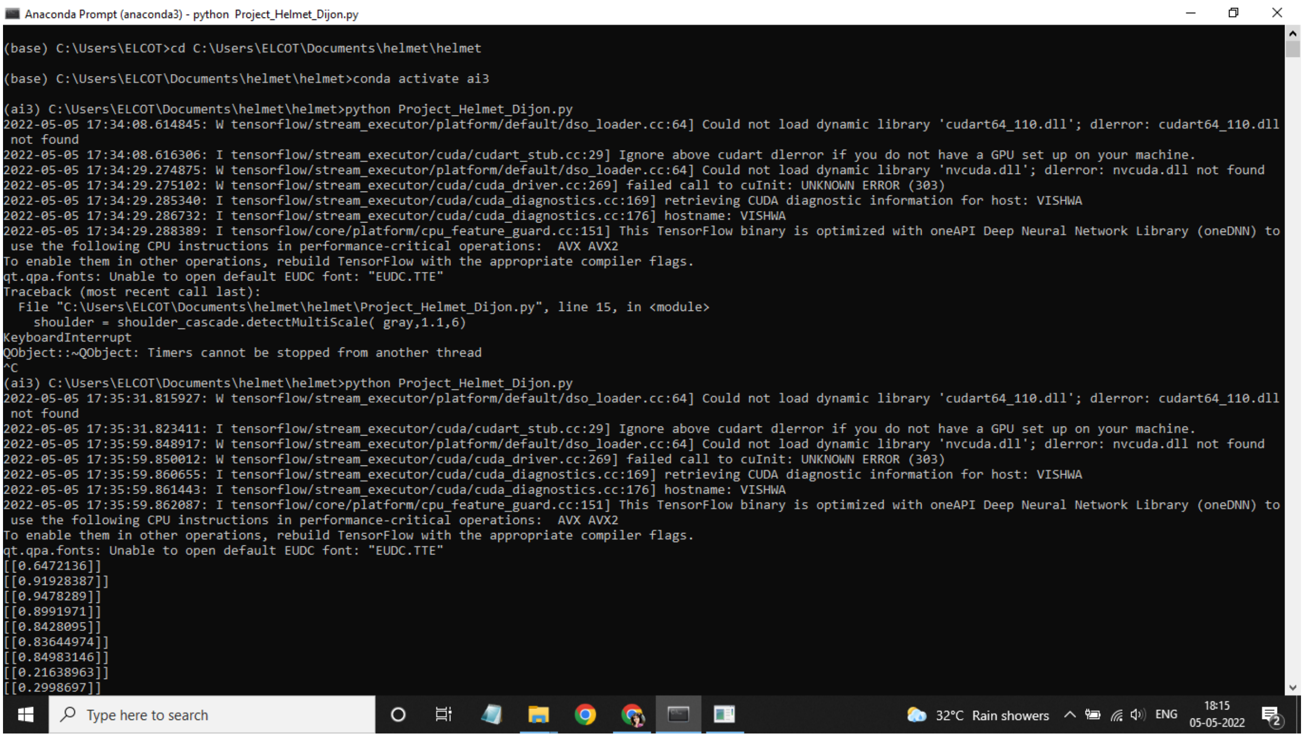


Figure 3 Result Module 3



Anaconda Prompt (anaconda3) - python Project_Helmet_Dijon.py

```
(base) C:\Users\ELCOT>cd C:\Users\ELCOT\Documents\helmet\helmet

(base) C:\Users\ELCOT\Documents\helmet\helmet>conda activate ai3

(ai3) C:\Users\ELCOT\Documents\helmet\helmet>python Project_Helmet_Dijon.py
2022-05-05 17:34:08.614845: W tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load dynamic library 'cudart64_110.dll'; dlerror: cudart64_110.dll
 not found
2022-05-05 17:34:08.616306: I tensorflow/stream_executor/cuda/cudart_stub.cc:29] Ignore above cudart dlerror if you do not have a GPU set up on your machine.
2022-05-05 17:34:29.274875: W tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load dynamic library 'nvcuda.dll'; dlerror: nvcuda.dll not found
2022-05-05 17:34:29.275102: W tensorflow/stream_executor/cuda/cuda_driver.cc:269] failed call to cuInit: UNKNOWN ERROR (303)
2022-05-05 17:34:29.285340: I tensorflow/stream_executor/cuda/cuda_diagnostics.cc:169] retrieving CUDA diagnostic information for host: VISHWA
2022-05-05 17:34:29.286732: I tensorflow/stream_executor/cuda/cuda_diagnostics.cc:176] hostname: VISHWA
2022-05-05 17:34:29.288389: I tensorflow/core/platform/cpu_feature_guard.cc:151] This TensorFlow binary is optimized with oneAPI Deep Neural Network Library (oneDNN) to
 use the following CPU instructions in performance-critical operations:  AVX AVX2
To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.
qt.qpa.fonts: Unable to open default EUDC font: "EUDC.TTE"
Traceback (most recent call last):
  File "C:\Users\ELCOT\Documents\helmet\helmet\Project_Helmet_Dijon.py", line 15, in <module>
    shoulder = shoulder_cascade.detectMultiScale( gray,1.1,6)
KeyboardInterrupt
QObject::~QObject: Timers cannot be stopped from another thread
^C
(ai3) C:\Users\ELCOT\Documents\helmet\helmet>python Project_Helmet_Dijon.py
2022-05-05 17:35:31.815927: W tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load dynamic library 'cudart64_110.dll'; dlerror: cudart64_110.dll
 not found
2022-05-05 17:35:31.823411: I tensorflow/stream_executor/cuda/cudart_stub.cc:29] Ignore above cudart dlerror if you do not have a GPU set up on your machine.
2022-05-05 17:35:59.848917: W tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load dynamic library 'nvcuda.dll'; dlerror: nvcuda.dll not found
2022-05-05 17:35:59.850012: W tensorflow/stream_executor/cuda/cuda_driver.cc:269] failed call to cuInit: UNKNOWN ERROR (303)
2022-05-05 17:35:59.860655: I tensorflow/stream_executor/cuda/cuda_diagnostics.cc:169] retrieving CUDA diagnostic information for host: VISHWA
2022-05-05 17:35:59.861443: I tensorflow/stream_executor/cuda/cuda_diagnostics.cc:176] hostname: VISHWA
2022-05-05 17:35:59.862087: I tensorflow/core/platform/cpu_feature_guard.cc:151] This TensorFlow binary is optimized with oneAPI Deep Neural Network Library (oneDNN) to
 use the following CPU instructions in performance-critical operations:  AVX AVX2
To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.
qt.qpa.fonts: Unable to open default EUDC font: "EUDC.TTE"
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```


Figure 4 Result Module 4

3. CONCLUSION

The proposed approach is to recognize single or different riders fundamentally all riders of a bike without wearing head protector from traffic observation recordings. SSD-Mobile Net model has been utilized for motorcyclist discovery. Then, at that point, the proposed lightweight convolutional neural organization recognizes wearing of protective cap or no cap for all cruiser riders. The proposed model functions admirably for head protector location in various situations with precision of 95%. This engineering performs equivalently well with other RCNN based cap identification techniques and can be stretched out in future to distinguish more convoluted instances of various riders including youngster riders. Further this work can be reached out to significantly more complicated situations of awful climate for discovery of helmetless motorcyclists.

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