

Automatic Detection of Helmet using RCNN and SSD Mobile Net

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Abstract: *Bicycle accidents were on the rise in a number of countries at the time. Over 37 million people ride bicycles in India. As a result, it's critical to develop a framework for automated head-protection detection for street safety. In this way, a bespoke article placement model is created based on a Machine Learning computation that can distinguish Motorcycle riders. The License Plate is extracted and the License Plate number is read using an Optical Character Recognizer when a Helmetless rider is discovered. This application can be run in stages, using information coming from a Webcam or a CCTV. Any intelligent traffic framework must include automated detection of offenders of traffic rules. Bike is one of the most important modes of transportation in a country like India, where the population density is great and cities are often vast. The majority of motorcyclists avoid wearing caps in cities or on highways. In the vast majority of motorcycle accident cases, wearing a cap can reduce the risk of head and severe cognitive harm to the rider. The great majority of traffic and safety violations are now identified by examining traffic recordings captured by reconnaissance cameras. This study presents a system for identifying single or many riders who ride a bike without wearing a helmet. In the suggested method, bike riders are identified in the first stage 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 the discovery of bike riders' head protectors in the following step.*

Keywords: Bicycle accidents

I. INTRODUCTION

1.1 Deep Learning

Deep learning techniques aim to learn highlight orders from more significant levels of the progressive system, which are affected by the production of lower level parts. Without relying only on human-created highlights, a framework can naturally learn complicated capacities planning the contribution to the result directly from information. Profound learning computations attempt to use the obfuscated structure of information circulation in order to uncover great representations, which are frequently at several levels, with higher-level learnt elements being distinguished from lower-level elements. The PC may learn muddled notions by creating them out of easier ones according to the progressive system of ideas. If we design a diagram to explain how these ideas are built on top of one another, the result is a multi-layered chart. As a result, we've coined the term "deep learning" to describe this approach to AI. On issue domains where information sources (and, unexpectedly, yield) are straightforward, profound learning reigns supreme. They are images of pixel data, reports of text data, or documents of sound data, 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 on-the-go discovery of a wellbeing protective cap. The SSD-Mobile Net computation, which is based on convolutional neural organisations, is used in the proposed technique. A dataset containing 3261 images of security head protectors is laid out and distributed to the general public. The images were taken from two sources: manual capture from the video checking system at work and open images acquired using web crawler technology. The image set is divided into three parts: preparation, approval, and testing, with an examining ratio of around 8:1:1. The findings reveal that the introduced deep learning-based model using 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(RCNN)

- Locales with convolutional neural organisations (RCNN), for example, 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 Convolutional Neural Networks.
- Mask R-CNN is one of seven tasks in the MLPerf Training Benchmark, a competition to improve neural network training speed.
- Rather than dealing with a large number of areas, the RCNN computation suggests a large number of boxes in the image and tests whether any of these crates have any information at any time.

Advantages:

- As a result, it recognises the important elements with little to no human intervention.
- For example, given a large number of photos of felines and canines, it learns certain elements for each class without the assistance of anybody else. Similarly, CNN is computationally efficient. Over 95% accuracy rate

1.3 System Architecture

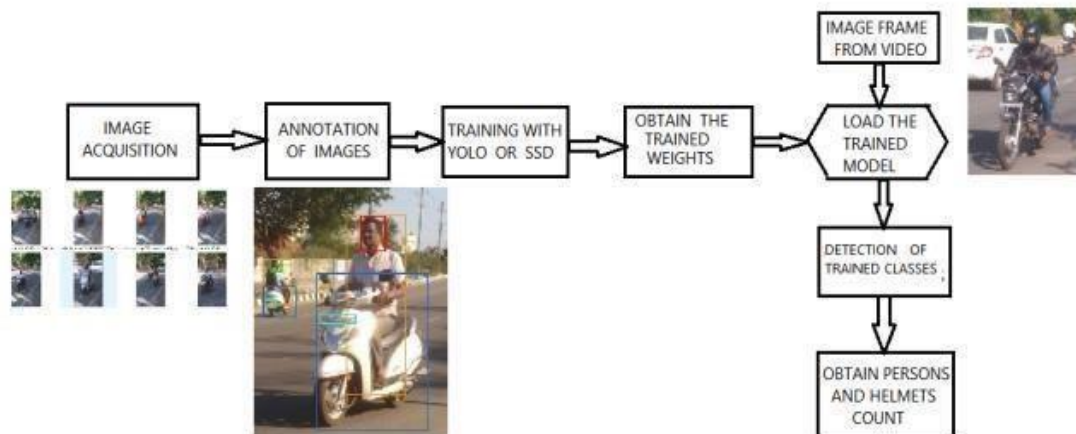


Figure 1 System Architecture

1.4 Modules

1.4.1 List of Modules

1. Training the Dataset
2. Open Camera and Open CV
3. Loading Model
4. Distinguish the wearing of Helmet or not
5. Identifying the accuracy of the helmet and non helmet

1.4.2 Module Description

1. Training the Dataset

With the dataset, the model is built using Tensor Stream and Keras (with and without Helmet)

2. Open Camera and Open CV

The open CV detects the faces of persons in the frame and uses the camera to monitor them.

3. Loading Model

The pre-prepared model is then layered to determine whether or not an individual has a Helmet.

4. Distinguish the wearing of Helmet or not

Using a pre-prepared model to determine whether or not a person is wearing the Helmet during a live video transfer with the use of a camera.

5. Identifying the accuracy of the helmet and non helmet

After identifying the helmet, the precision of the border box will be predicted. The accuracy forecast will be derived by comparing the testing data with pre-trained data.

1.5 Predict the Result

Subsequent to investigating the remarks, this module assists with showing the ideal outcomes to the client.

1.6 Implementation

The task's execution phase is when the notional plan is turned into a working structure. As a result, it might be considered the first step towards creating a successful new framework and assuring the client that the new framework would operate. The execution stage includes 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 examinations are present at the time of execution of any framework. They have been confirmed to be capable of regulating various activities of individuals outside of their own information processing departments.

1.7 Result Screenshots

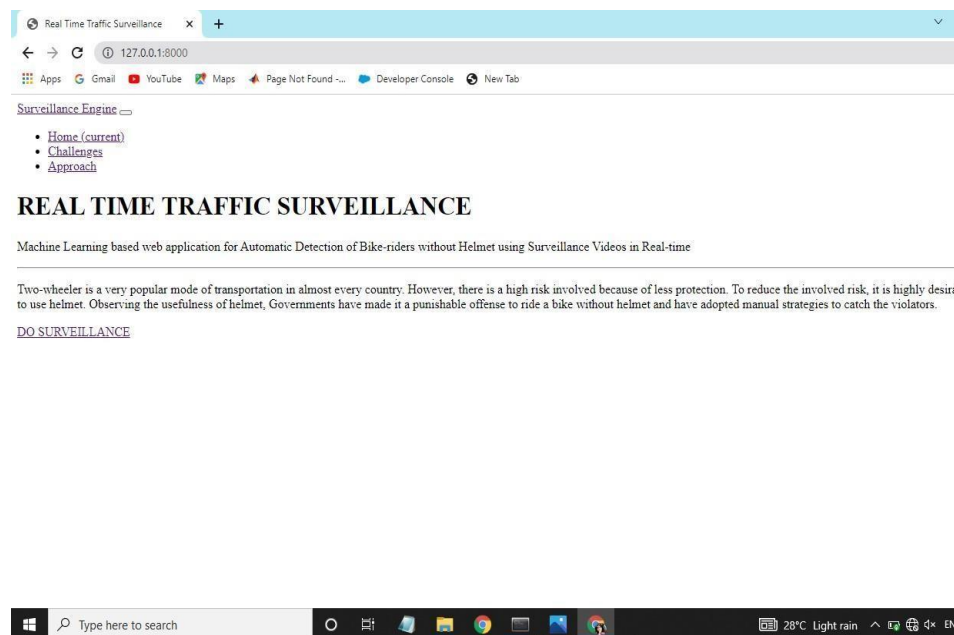


Figure 2 Result Module 1

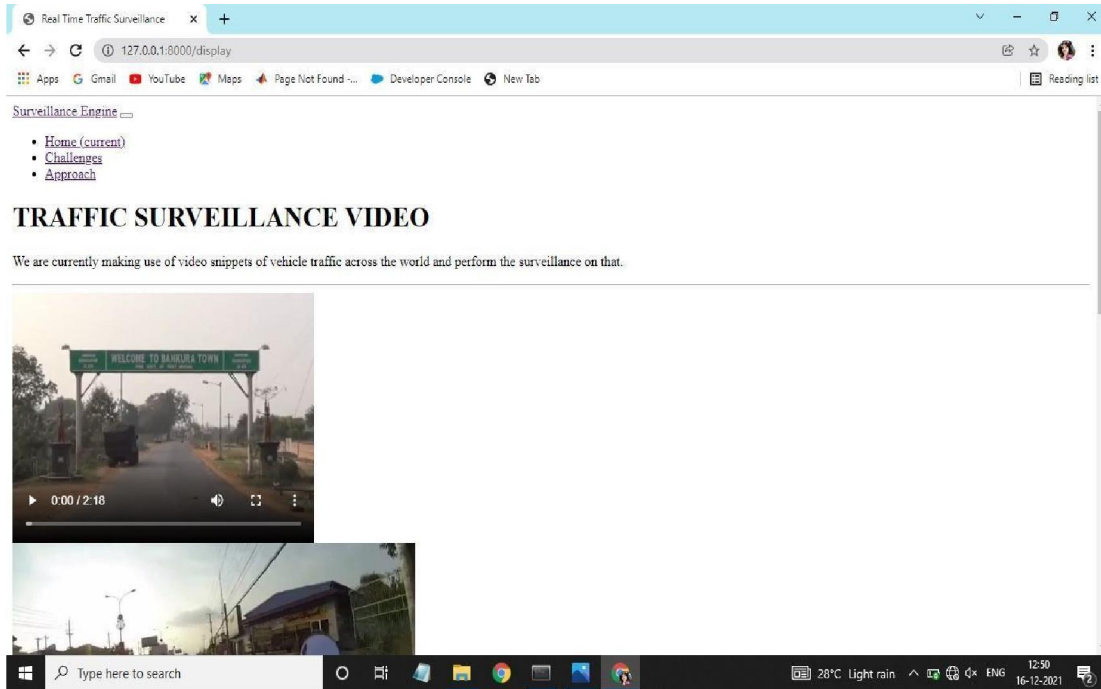


Figure 3 Result Module 2

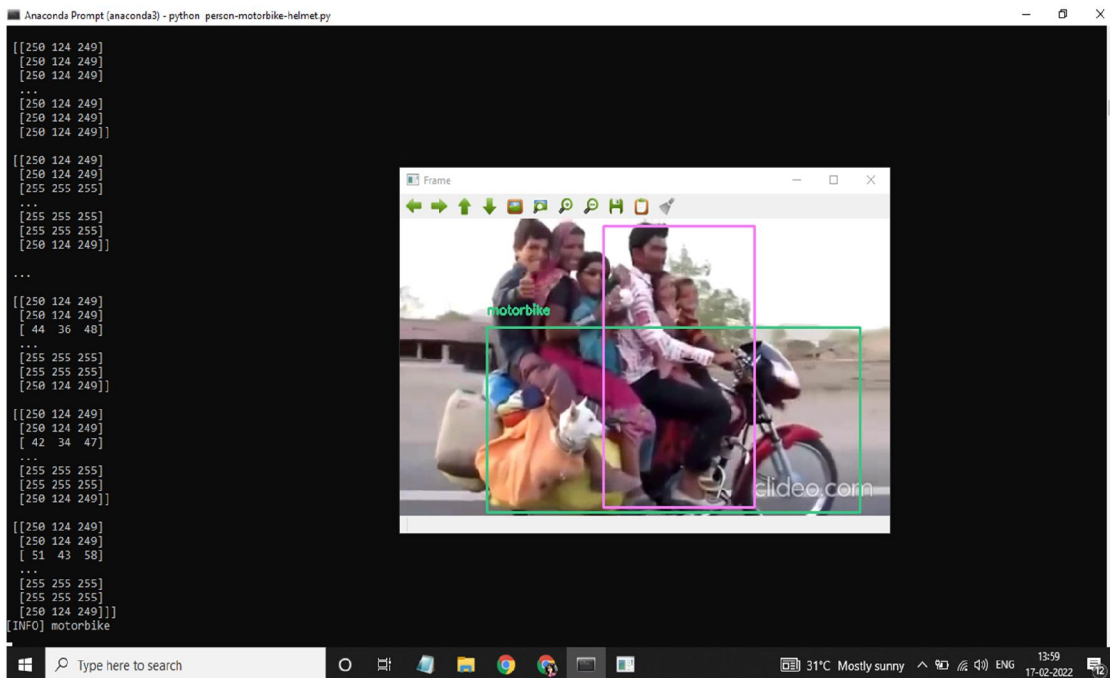


Figure 4 Result Module 3

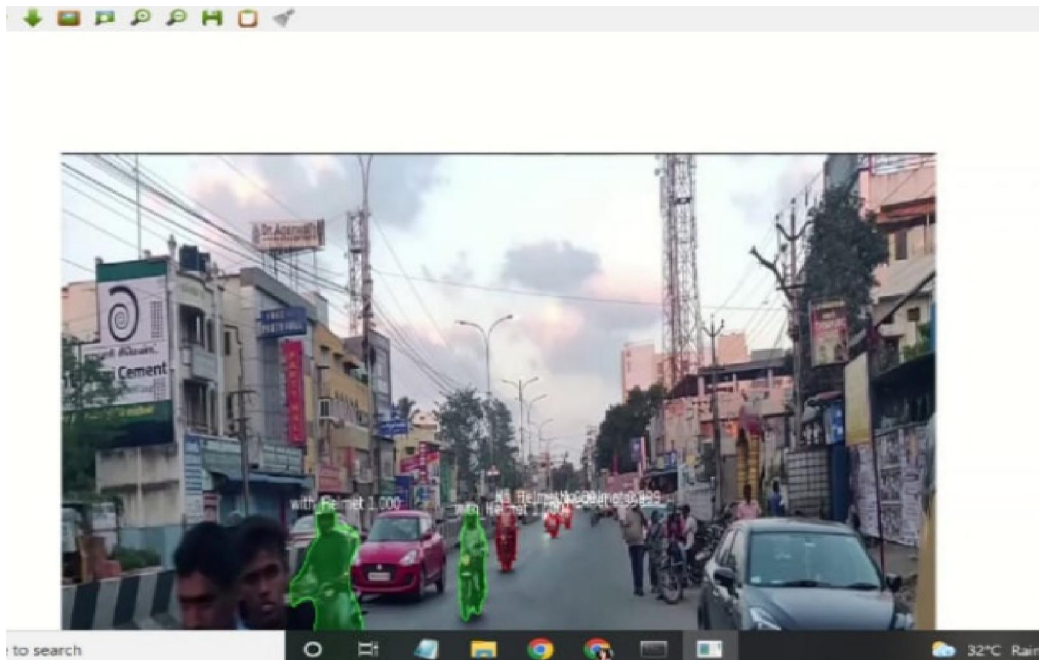


Figure 4 Result Module 4

1.8 Conclusion

The suggested method uses traffic observation records to identify single or many riders who are not wearing a helmet. The SSD-Mobile Net concept was used to find motorcyclists. The suggested lightweight convolutional neural structure then recognises whether or not all cruiser riders are wearing a protective headgear. With a precision of 95%, the suggested model performs brilliantly for head protection positioning in diverse conditions. This technology compares favourably to previous RCNN-based cap detection algorithms and can be expanded in the future to distinguish more complex riders, including children. This approach can also be applied to far more challenging conditions involving bad weather for the detection of helmetless bikers.

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