Deep Learning-Based Automatic Helmet and Number Plate Recognition

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***Abstract*—In addition to wearing helmets, which reduce the risk of severe head and brain injuries by absorbing the force of a force or collision to the head, motorcycle riders must take additional precautions to protect their bodies. Riders and passengers who wear helmets have a considerably higher chance of surviving an accident than those who do not. Every motorcycle rider is required by law to wear a helmet at all times. However, a lot of biker's disregard and operate their vehicle without any form of defense. The policeman tried to manually regulate the situation, but it was insufficient given the actual situation. Despite the recent requirement for helmets, many people continue to operate motor vehicles without them. Since helmets are the primary piece of safety gear used in developing nations, the number of fatalities has increased every year. Wearing a helmet is the greatest way to reduce fatalities and brain damage from motorcycle and cycling accidents. Motorcycle operators incur a high danger of suffering fatal head injuries if they don't wear helmets. In addition to the additional expenses that helmet-less motorcyclists inflict on hospitals, the cost of the incapacity caused by severe head injuries affects individuals, families, as well as their careers and social lives. In order to track which motorcycles are wearing helmets and which are not, we employ deep learning algorithms CNN and DenseNet Model to identify those that are. Further to achieve greater accuracy we compare both the deep learning algorithms. For the Number Plate detection YOLO is used.**

***IndexTerms*—Deep learning algorithm, Helmet Detection, YOLO, CNN, Dense Net Model**

I. INTRODUCTION:

Riders frequently disregard road safety worldwide, motorcycle accidents have been rapidly increasing over the years in various nations, resulting in accidents and fatalities. Most nations have legislation requiring the use of helmets for two-wheeler riders to address this issue. Therefore, it is crucial for motorcycle riders to comprehend the dangers of riding without a helmet. The danger of traumatic brain injury is highest among riders who do not wear helmets because, in the event of an accident, the head is vulnerable to a terrifying hit. There is a law in India that requires helmet use exclusively for drivers, not even for passengers. Anyone riding a motorcycle without a helmet runs the risk of being in an accident or suffering head trauma. Everyone should be required to wear a helmet, even youngsters.

Therefore, in the area of Computer Vision, we have created a system that is based on TensorFlow to enforce this. The system can determine whether motorcycle riders are wearing helmets. If any of them are present and not wearing helmets, the system will carefully assess the circumstances and flag the infraction.Motorcycle riders must take additional steps to safeguard their bodies in addition to wearing helmets, which aim to lower the risk of major head and brain injuries by absorbing the force of a force or collision to the head. Wearing a helmet significantly increases a rider's and passenger's chance of survival over those who do not. Every motorcycle rider is required by law to wear a helmet at all times. However, a lot of bikers disregard and operate their vehicle without any form of defense.

The traffic police attempted to manually control the situation, but given the circumstances, it was insufficient.Despite the recent requirement for helmets, many people continue to operate motor vehicles without them. The number of fatalities has been rising every year, especially in developing nations where many riders fail to wear helmets, which are the primary piece of safety equipment for both riders and passengers. Wearing a helmet is the greatest way to reduce fatalities and brain damage from motorcycle and cycling accidents. Motorcycle operators incur a high danger of suffering fatal head injuries if they don't wear helmets. In addition to rising medical costs for motorcycle riders who don't wear helmets, the cost of disability caused by severe brain injuries affects individuals, families, careers, and society. Helmets are frequently required solely for riders, according to Ministry of Road Transport and Highways.

Fig. 1. Helmet Standards Breach

The guidelines for wearing a helmet for motorcycle safety are shown in Fig. 1. The requirement that is missing from the figure but might be added as a road safety law should also apply to passengers.

Fig. 2. Helmet regulations to be followed

The exact standards that should be adhered to by everyone for increased safety are shown in Fig. 2. There are several systems that have been proposed and that could be put into place that would make wearing a helmet mandatory if you arrived without one. If a barrier is connected to the system and only opens if no violations have been found, the system can be put into use. At all costs, it may require the riders to wear helmets with their passengers.

II. RELATED WORK:

Despite the fact that motorcycle safety helmets are well known for reducing head injuries, usage of motorcycle helmets is low in many nations since there aren't enough police to enforce helmet rules. This study describes a system that can recognize motorcycle riders and assess whether or not they are donning safety helmets. Based on features collected from their region attributes using the K-Nearest Neighbor (KNN) classifier, the technique extracts moving objects and categories them as a motorcycle or other moving things. On the basis of projection profile, the heads of the riders on the identified motorcycle are then numbered and segmented. Based on data extracted from 4 regions of the segmented head region, the system uses KNN to categorise the head as either wearing a helmet or not.[1]

For a power substation to be safe, surveillance is crucial. The main element of the entire intelligent surveillance system in the power substation is the detection of whether perambulatory personnel are wearing safety helmets or not. Using computer vision, machine learning, and image processing, an innovative and useful safety helmet detection framework is proposed in this research. The ViBe background modelling technique is used in power substations to identify moving objects. Additionally, real-time human classification framework C4 is used to find pedestrian accurately and swiftly in power substation based on the results of motion objects segmentation. Finally, utilising the head location, the colour space transformation, and the discrimination of colour features, the safety helmet wearing detection is implemented in accordance with the results of pedestrian detection.[2]

One in five worker deaths in private business in the United States occur in the construction sector, making it the industry with the highest fatality rate. The industry, the country, and the families of the workers have all suffered tremendous damage. The need for inventing creative ways to automatically monitor the safety of workers at construction sites is increasing given the size and number of building projects being carried out in the U.S. The wearing of a protective helmet is required in construction work since the head is the most important part of a person's body and is most vulnerable to a collision that could result in serious injury or death. This study aims to automatically identify the applications of construction helmets. (for instance, if the worker is wearing a helmet or not) by looking through the surveillance footage taken during construction. We first identify the object of interest (a construction worker) based on the photographs gathered, and then, using computer vision and machine learning techniques, we determine whether the worker is wearing a helmet or not. Construction worker detection is accomplished in two steps: first, frequency domain data from the image is combined with the well-known human detection algorithm Histogram of Oriented Gradient (HOG), and second, a combination of color-based and Circle Hough Transform (CHT) feature extraction techniques is used to identify the construction worker wearing a helmet.[3][4].

The identification of traffic rule offenders is a highly desirable but tough job in order to provide safety measures because of many challenges such opacity, lighting, poor quality of surveillance video, fluctuating weather patterns, etc. In this article, we describe a system for automatically spotting motorcycle riders operating their vehicles without protective helmets on security footage. In the suggested method, we first extract moving items from video frames using adaptive background subtraction. Motorcycle riders are afterwards chosen from the distant vehicles using convolutional neural networks (CNN). Again, we use CNN on the top one-fourth part to further recognise motorcycle riders operating their vehicles without even a helmet.

III. PROPOSED METHODOLOGY:

A. System Architecture:

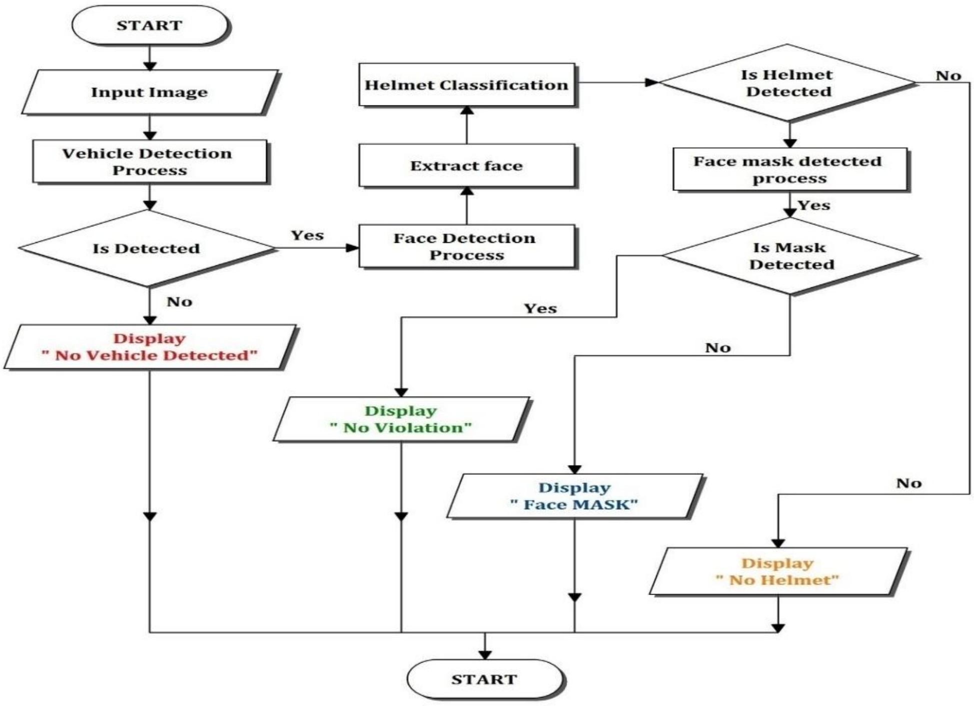

Fig 3: System Framework

The three processes that make up our suggested method for detecting helmet use on tracked motorcycles are shown in Fig. 3. Our method's initial stage involves the recognition of active motorcycles, or motorcycles with at least one rider on board, on a single frame level using a fine-tuned pre-trained DensenNet [10]. The face with the helmet is removed, cropped, and then tested for helmet detection in the second stage. YOLO[9] is used to retrieve motorcycle number plates in the final step.

The job of finding a motorbike in a particular image is a frequent item detection task. We developed a cutting-edge algorithm for detecting objects to recognise motorbikes in the dataset in order to do this, as shown in Fig. 1. Modern algorithms for detecting objects fall into two basic categories: first and second stage. Two-stage approaches are slower despite typically having a greater item detection performance because pictures are analyzed twice: once to locate prospective items and again to find them.

B. CNN MODEL:

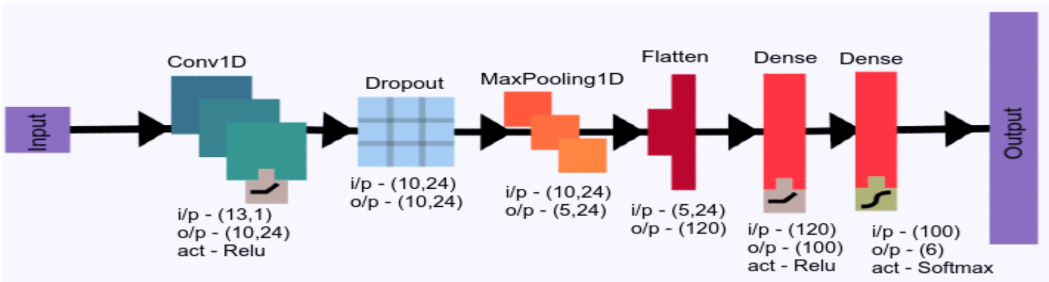

Fig 4: CNN Model Architecture

CNNs, a subtype of Dnns, are commonly applied to the processing of visual images. CNNs are able to recognise and classify particular aspects in images. Natural language processing, picture categorization, movie and picture analytics for clinical uses,and multimedia content identification are some of their applications.

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In mathematics, inversion is the act of combining 2 purposes in order to obtain a tertiary equation that takes how and why the shape among one function is changed by the second. Pooling layer is the name CNN uses to describe this arithmetic operations.

Two pictures which can be expressed as vectors are combined to create an outcome in order to obtain characteristics from a photo.

Below following are brief summaries within each different strata:

- Next learning algorithm is used to extract features from the input. Each gradient information representations is a scalar number of Thirteen groups. The convolutional kernels is blended in this instance to get a number of activation feature maps from the layer above. In our design, we used a convolution kernel size of 4.
- Leave school: A small set of each batch's outputs is negated in order to avoid large connections among subsets of consecutive layers.
- Dropout improves a pattern recognition effectiveness of the algorithm because it lessens overfitting by making the system simpler. The artificial structures' neurons are taken out at training.
- The max pooling decreases the dimension of the features and abstracts them by combining the convolution layer. Subsequently, the overfitting issue is avoided, and computation speed is also increased

This point cloud is used to extract the largest portion in 3×3. Through max filter, the average of the elements in a section of an image with a predetermined size is calculated. Amount Bundling calculates the items' cumulative sums inside the particular section. The Median Filter frequently serves as a bridge between the FC Layer and the Convolutional Network.

The generalization of the traits retrieved by that of the CNN model with in Neural technique enables the networks to recognize the properties on their own. This helps a network's calculations run more efficiently.
In this instance, the input (5*24) was flattened.

A 120-pixel wide feature space is produced by extracting the larger particles and condensing it to a single vector.
The tier in the densities level of said RNN thus absorbs information from every synapse in the plane above, making it the layer only with closest linkages. This barrier is composed of an input layer from either the layer before, a weight matrix W, and a bias vector b.

Statistical technique uses a normalized exponential function called Max - pooling policies that enable and encourage. By utilizing the Perceptron, the matching outcome component from the Neurolinguistic programming star must adhere to the sample class (in our case, the output vector is 6).

To identify and approximate any kind of continuous and complex link between network variables, activation functions are used. It defines which model information should advance and which should not at the network's end, to put it simply.

C. Dense Net Model:

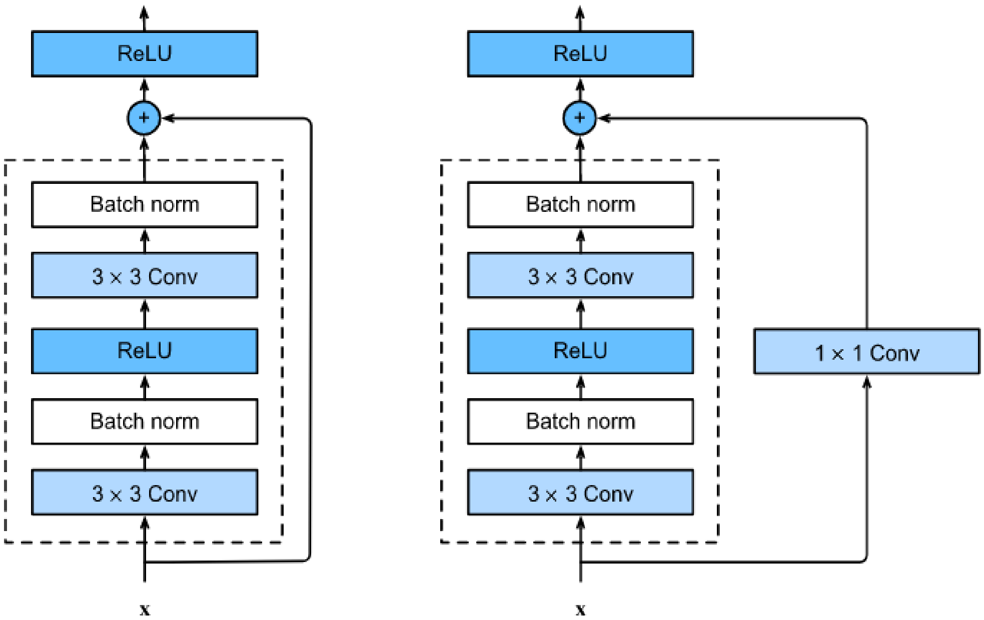

Fig 5: DenseNet Architecture

Below following are brief summaries for every different strata:

• Next learning algorithm is used to extract features from the input. Each gradient information representations is a scalar number of Thirteen groups. The convolutional kernels is blended in this instance to get a number of activation feature maps from the layer above. In my design, we used a convolution kernel size of 4.

• Leave school: A small set of each batch's outputs is negated in order to avoid large connections among subsets of consecutive layers.

Pooling layer improves a pattern recognition effectiveness of the algorithm because it lessens generalization error by making the system simpler. The artificial structures' transistors are taken out at development.

• The max pooling decreases the dimension of the features and abstracts them by combining the convolution layer. Subsequently, Therefore, a Dnn will still have between L and L plus L(L+1)/2 links. We might swiftly train a model with more than 100 layers using this strategy, which minimises the dimensionality of such attributes as well as abstraction it so a thick network has almost no elements than for an intermediate representation. Likewise

$$A[l] = g(A[0],A[1],A[2],\ldots A[l-1])$$

Going deeper into the network makes this somewhat unsustainable because when you move from the second to the third layer, the third layer absorbs information from both the second and the prior layers as well.

Suppose there are ten levels altogether. Lastly, mostly on 10 stages, we must include all of the feature maps from the first eight rows. If we create 128 convolution layers for each of these, there is a feature map inflation.

We created a dense block here in order to solve this issue. As little more than a outcome, every density blocker has a specific layered structure, but a layer known as a transitioning layer receives the output from each dense block. akin to reducing the dimension of the maps using Max pooling and then one-by-one convolution the transitioning layer enables Maximum sharing as either a by-product, which often results in a smaller width for you extracted features.

In the example Fig 5, the convolution layer and pooling layer are the first two blocks, while the transition layer is made up of combinations of the two.

Consequently, the dense net has the following benefits.

- Efficiency of parameters: Only a small number of parameters are added by each layer; for instance, each layer only learns roughly 12 kernels.
- Deep implicit supervision Enhanced gradient flow through the network- All layer feature maps have direct access to the gradient and loss function.
- Growth rate: This controls how many feature maps are generated as separate layers inside dense blocks.

Composite functions - The following is the order of operations inside a layer. So we have batch normalisation, Relu application, convolution layer (which will be one convolution layer).

D. YOLO:

This technique classifies its item using YOLOv2[5], that had 19 convolutional layers, 5 max-pooling layers, and softmax activation parameters. This provided image has been split into SxS data points. Each cell containing the item's center predicts the 5-bounding box (BB) coordinates (b, b, b, b, c). The origin of such item in regard to the position of data point is shown by the parameters (b, b), and the object's width and height in proportion to the dimension of the photograph are shown by the variables (b, b). Whether an object is present in a grid cell is indicated by the gained strength c. An illustration of the procedure is depicted in Fig. 6.

The yellow grid box in Fig. 6 is in charge of foretelling.
the LP because it houses the LP's centre (black dot). The initial grid cell, which contains the centre of LP, is represented by the coordinates (,). Using Eqs, the BB's real coordinates were normalised with respect to grid cell location Eqn. (1)–(4):

$$b_x = (b_x - c_x) / c_x \ldots\ldots \text{ Eqn 1}$$
$$b_y = (b_y - c_y) / c_y \ldots\ldots \text{ Eqn 2}$$
$$b_w = b_w \ / \ W \ldots\ldots\ldots\ldots \text{Eqn 3}$$
$$b_h = b_h \ / \ H\ldots\ldots\ldots\ldots \text{ Eqn 4}$$

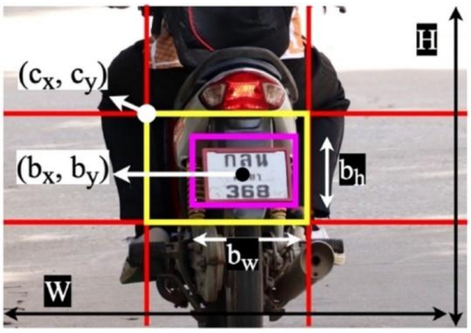

Fig 6 : YOLO Numberplate Detection

IV. EXPERIMENTAL RESULT:

The system has been tested with a variety of frames, including helmet, no-helmet, head, weft-covered head, and multiple head or helmet frames. The simulation looks like this:

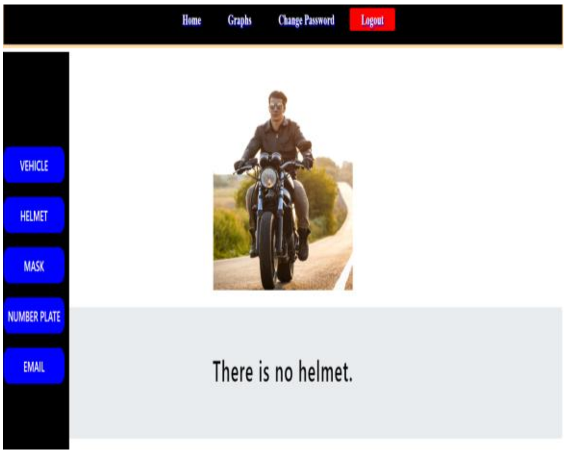

Fig 7: No Helmet

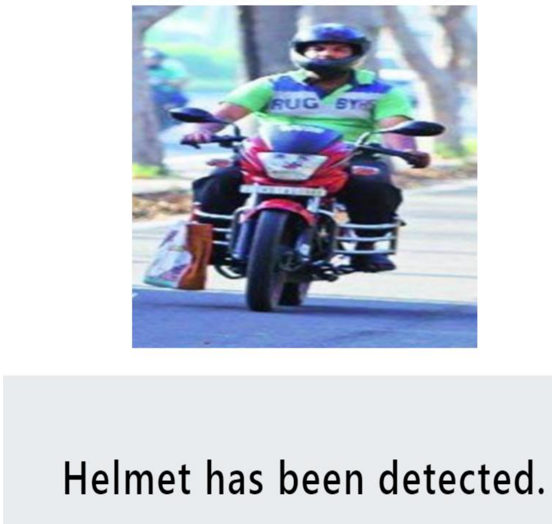

Fig 8: With Helmet

Before applying CNN and Dense Net algorithms in Figs. 7 and 8 , we crop the images of the facebefore looking for helmets. Then apply CNN and Dense Net models to the images to predict the images with or without helmet.

Fig 9:With Helmet and Number Plate

Fig 10: Without Helmet and with Number Plate

In Figs. 9 and 10, the number plate is found using YOLO, which takes a clear picture of the license plate in front of the car, after a helmet is found.

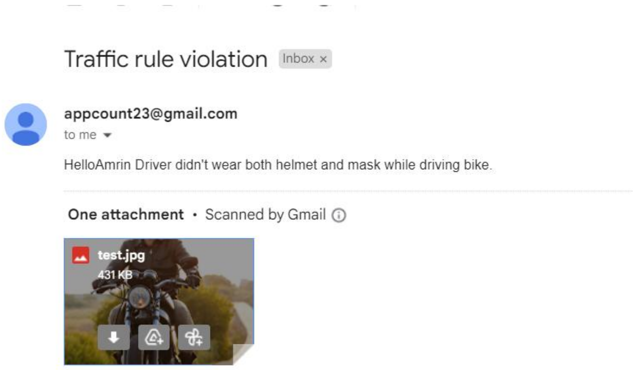

Fig 11: Mail sent to user account

When all infractions have been found, an email is sent to the user's registered email address, which was used upon registration. The Simple Mail Transfer Protocol (SMTP) is used to transmit emails over the internet. SMTP is an application layer protocol that emphasises connections. Email transmission via SMTP is dependable and efficient. The transport layer protocol utilised by SMTP is TCP. It controls email server communication over a TCP/IP network for both sending and receiving messages. In addition to email transmission, this protocol provides the option of email notifications. An email is sent from the sender's mail client to their mail server, which then sends it over SMTP to the recipient's mail server.

Table 1 : Result Analysis for CNN Model.

Classification Report	precision	recall	F1-score	support
0	1.00	0.78	0.88	91
1	0.84	1.00	0.91	106
Accuracy			0.90	197
Macro avg	0.92	0.89	0.90	197
weighted avg	0.91	0.90	0.90	197

As shown in Fig 14, the accuracy of CNN model is 90%, Precision which is a useful metric and shows that out of those predicted as positive, how accurate the prediction was is 91%.And Recall which is the ratio of correctly predicted outcomes to all predictions is 90%.

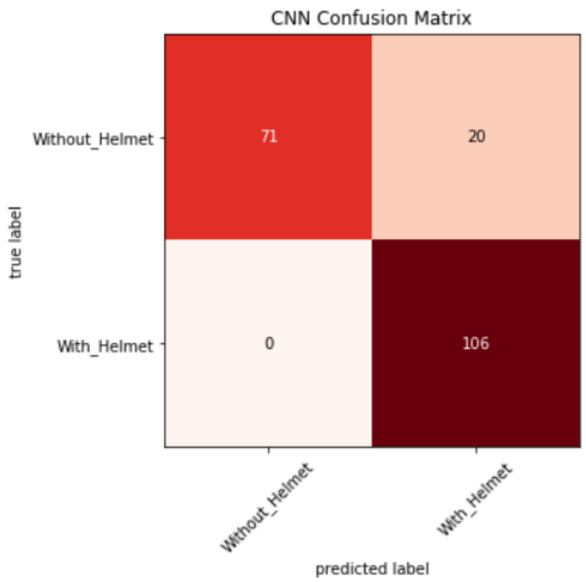

Fig 15: Confusion Matrix for CNN Model

The above Fig shows that 177 images were predicted correctly and 20 images were incorrectly predicted.

Table 2: Result Analysis For DenseNet Model

Classification Report	precision	recall	F1-score	support
Without Helmet	1.00	1.00	1.00	91
With Helmet	1.00	1.00	1.00	106
Accuracy			1.00	197
Macro avg	1.00	1.00	1.00	197
weighted avg	1.00	1.00	1.00	197

The accuracy of the DenseNet model, as shown in Fig. 15, is 99%.The prediction's accuracy is99%. Recallis also 99%.

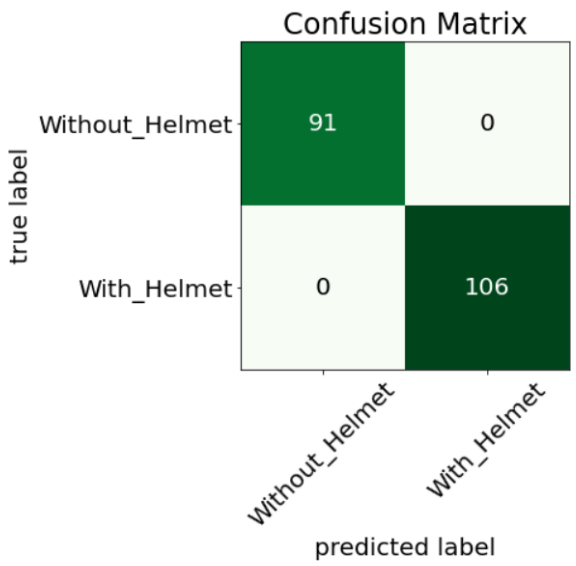

Fig 13: Confusion Matrix For DenseNet Model

According to the Fig. above, 197images were accurately predicted, while 20 images were wrongly forecasted.

V. CONCLUSION:

In this article, we present a deep learning-based system to automatically carry out three human observer motorcycle helmet use registration tasks, including motorcycle detection, helmet identification, and numberplate detection. Additionally, we have used our method to analyse image data from various road environments that contained problematic elements like occlusion, different camera angles, an unbalanced number of coded classes, as well as different rider counts per motorcycle and different traffic volumes. Our method is more thorough than past methods for the automatic detection of motorcycle helmet use thanks to all of these factors. Our findings indicate that our method generally has good accuracy.

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