Advances and Applications in Mathematical Sciences
Volume 21, Issue 10, August 2022, Pages 5811-5823

AUTOMATED TRAFFIC RULES FOR ROAD SAFETY USING IMAGE PROCESSING

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Abstract

Recent technological advancements in computer vision, object detection and recognition have led to a transformation in the way humansper form day to day activities. From the traditional way of doing cumbersome tasks manually, these technologies have given birth to automating various processes that may or may not require intelligence and reduce human error while performing the same tasks. Consequently, this paper presents an application of computer vision to develop a helmet detection and number plate recognition system that helps traffic police to catch hold of the two-wheeler rule violators. Hence a database will be available for analysis by the police authority. The research is focussed towards building a helmet detection system that uses car segments to detect motorcyclists and use the YOLOv5 algorithm to determine whether people are wearing helmets or not. While attaining these goals, the focus was towards achieving high speed and accuracy of object detection along with image classification and object recognition. Integration of YOLOv5 and ResNet50 in this model have helped us achieve this goal.

1. Introduction

Computer Vision is a computer science software program that understands and detects images and scenes. Computer Vision is built with various features such as object detection, image recognition, image production, high image editing etc. Object discovery is the most significant and crucial aspect of computer vision due to the number of applications that occur. Object discovery is a computer-aided detection method for detecting events in images or videos. These techniques are helpful in critical applications like border security where it can be utilized in automated surveillance system [1]. Existing algorithms often use machine learning or in-depth learning to produce meaningful results. When people look at photos or

2020 Mathematics Subject Classification: 68T01.

Keywords: Computer Vision, Object Detection, Image classification and recognition, YOLOv5, ResNet50, Helmet Detection, Number Plate Recognition.

Received April 10, 2022; Accepted May 15, 2022

videos, we can see and discover our favourite things in a moment. The goal of object acquisition is to substitute this intelligence using a computer.

Road rules play a major role in ensuring road safety. With so many pedestrians on the road, it is almost impossible to track down people who violate road safety rules, one of the rules we can investigate here is, a two-wheeled passenger helmet. In a developing country like India people prefer two-wheeled over other vehicles as they are more affordable and have lower maintenance costs. According to the Data Intelligence Unit (DIU) in 2017 [2] more than 45000 motorcyclists passed away in road accidents, of which 73.8% of them were found not wearing helmets. Traffic police take photographs in person to track down the number of vehicles to put on the challan. The automation of this process will reduce the work of traffic cops and catch more traffic offenders than ever before. We hope that this will force people to take the rules and regulations of the road seriously and help managers in issuing tickets that break the hat effectively.

The major focus of this research is to develop and implement a system that detects helmet of two-wheeler riders and creates a database of the number plates where a rider is spotted without a helmet. The purpose of this system is to reduce the load on traffic police who manually take pictures to track the vehicles' number to file challan. For this purpose, object detection and classification techniques are utilized to automate the traffic regulation for at least the two-wheeler passengers. The automation process requires in-depth learning and that is based on neural activity networks and has the same or similar concepts as neural activity networks. This paper discusses two types of in-depth learning algorithms. These are YOLOv5 and ResNet50 and these have been utilized for helmet detection and number plate recognition. The paper is structured as follows: Section 2 combines background work with previous research findings using object detection techniques and the affected domain. Section 3 presents the proposed research methodology and the algorithms used for object detection. Section 4 describes the functional structure of the model followed by the test results and the conclusion and future activity in section 5 and 6 respectively.

2. Literature Review

Till date several researchers have worked on object detection and classification algorithms. Many of them have been utilized in critical domains like tumour detection, surveillance systems and tracing the traffic rule violators. Below we discuss the techniques and the methods used by them.

Deep learning for image processing has been utilized in several application domain to automate the process of recognition for validation [3] [4]. The success of these techniques to image recognition has given rise to numerous approaches that are utilized for object detection and tracking while in motion. These techniques not only automate the process, but they also make accurate and precise assessment of the image. Convolution neural network is the state of art technology for image and object recognition and have been used with several optimizers for giving better results [5]. Like bike riding situation multi-object tracking algorithm is proposed in a sporting event by Moon et al. [6]. Dahiya et al. [7] apply a convolution neural network to track a motorcyclist with and without a helmet. But in this case the need is to train CNN accurately to distinguish between the helmet and the non-helmet which is a time-consuming task. Chiu et al. [8] used a computer-based program aimed at locating and separating motorcycles from another vehicle. A helmet detection system was used where the presence of a helmet made it easier for a motorcycle to be located. The paper finds the edges of the helmets and lists the possible location of the helmet.

To cater to the challenges associated with moving objects Tao et al. presents global motion estimation technique for the extraction of moving object [9]. Agrawal et al. [10] used optical flow and eigenface using low resolution video. Wen et al. [11] suggested a method of obtaining a circular arc based on the Hough mutation. They used it to discover the existence of a protective helmet on the Automatic Teller tracking system. But the drawback of this work is that only geometric features can be used to determine the presence of a protective helmet. But, geometric features are not sufficient to identify the presence of a protective helmet; most of the times, the head can also miss the helmet. Chiu et al. [8]. Only use the Circular Hough Transform to determine the presence or absence of a helmet at the scene that are divided by any round object at the scene. But on the road, there are many round objects other than the motorcycle rider's head which were also classified as a helmet. Karwal et al. [12] proposed a vehicle number plate detection system in which he used a standard parallel component to match the template in order to address the problem of measuring and recognizing letters under different positions, but the result of this function was used consistently to match the template. Silva [13] proposed a helmet acquisition model that begins with classification of a moving object using adjectives and then obtains a tracking helmet (ROI) and the limitation was that it used a circular Hough transform to distinguish between a helmet and a non-helmet which also led to incorrect separation between the head and the helmet as both have a circular shape and are mathematically costly. Comparative analysis of some of the helmet and number plate detecting systems has been presented in table1 below.

Table 1. Comparative analysis of helmet and number plate detecting system.

Sl.No.	Author and Year	Title of the Paper	Key Highlights	Limitations
1	Dahiya et al. 2016	Automatic detection of bike riders Without helmet using surveillance videos in real-time	Works in real time Uses object segmentation Less expensive	Time consuming Separate training required
2	Chiu et al., 2017	Motorcycle detection and tracking system with occlusion segmentation	Uses visual length, width etc Works for moving objects	Occlusion issue exists in detection
3	Wen et al., 2013	The safety helmet detection for ATM's surveillance system via the modified Hough transform	Uses geometric features of helmet Apply circle detection algorithm for detection of helmet	Only geometric features can be used. Many times, head and helmet can be falsely detected
4	Karwal et al., 2015	Vehicle number plate detection for Indian vehicles	Uses threshold partitioning for character on number plate Takes into account the correlation between the templates for character spacing	Template matching only posses limitation related to variety and is expensive

5	Silva et al.,2014	Helmet Detection on Motorcyclists Using image descriptors and classifiers	Object segmentation Region of interest identified Works on selected region	Uses circular Hough transform to separate head and helmet , can give wrong results
6	Gnanaprakash et al., 2021	Automatic number plate recognition using deep learning	For real time, moving objects Deep learning methods	Works as black box, dataset should be huge

3. Proposed Methodology

The first step in the development of helmet detection and number plate recognition is to take input video and then extract frames from the regions of interest. The extracted frames are then processed for object detection. For object detection, prior to the existence of YOLO there were many two-stage proposal-based algorithms like RCNN and its variations. They first propose the possible object region and then classify the images in those regions. Even though the average precision of these two stage algorithms is remarkable they are very slow in performance as they make multiple iterations. On the other hand, YOLO is a neural network to perform discovery without certain features and is based on CNN. It is a one stage proposal free algorithm and performs all the predictions using single fully connected layer in a single iteration.

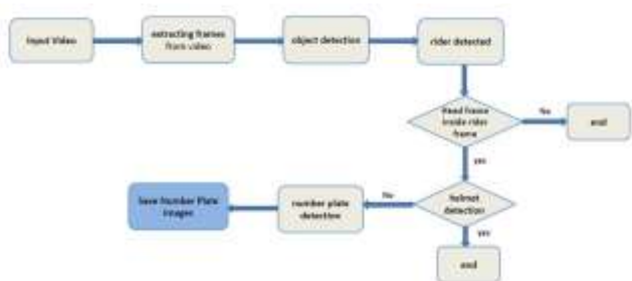

Figure 1. Flowgraph of the model.

Even though YOLO struggles with the identification of small objects present in clusters and may not give good accuracy in such situation, it has been found suitable for the application domain discussed in the present work. YOLOv5 is good for finding an object but not for dividing an object. Therefore, ResNet50 is used as an image classification algorithm to get better results. ResNet is a convolutional neural network which enable the use of extremely deep neural networks by overcoming the vanishing gradient problem of CNN. ResNet uses Skip Connection to overcome the problem. ResNet50 has 48 convolution layers and oneMaxPool and one Average Pool layer. This architecture is found suitable for image classification and object localization with reduction in computational expense.

For object detection the present work uses YOLOv5 pretrained model. Once the rider is detected, image classification is performed to classify the rider wearing or not wearing helmet. In the present work Resnet50 is used as image classification algorithm for better accuracy of results. The following sections presents the detail description of these two algorithms.

3.1 YOLO. YOLO stands for You Only Look Once, a convolutional neural network (CNN) that identify real-time objects with significant accuracy. This method uses a single neural network to process the whole image, then divide it into sections and predict binding boxes and opportunities for each component. These binding boxes are weighted with the expected possibilities. YOLOv5 is fast, which makes it an immensely powerful model for finding something, which is why it is the most useful algorithm in our system.

3.1.1 YOLOv5 ALGORITHM. YOLOv5 is listed in the Pytorch framework. It is a single-stage detector, with three key components such as any other single-stage device namely Model Backbone, Model Neck, Model Head. The Model Backbone [14] is used to extract important features from a featured image provided. In YOLOv5 CSP-Cross Stage Partial Networks is used as the backbone to extract the instructive features from the input image. The structure of the YOLOv5 network is split into 4 parts: enter, spine, neck, and forecasting [15].

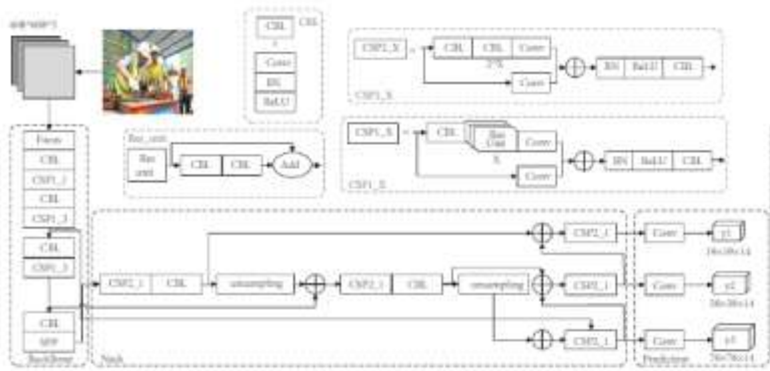

Figure 2. Structure of YOLOv5 [15].

YOLOv5 adds Mosaic records enhancement to the information access thing; recognition shape and CSP structure are used in the back of the bone; FPN + PAN structure is added to neck; the prediction segment enhances the function of the binding box loss from CIOU_Loss to GIOU_Loss. Taking the YOLOv5s community model for example, the spinal community makes use of the CSP1_1 and CSP1_3 structure [16], and the neck uses the CSP2_1 architecture to increase integration among networks. The network shape of the YOLOv5 is shown in figure 2.

3.2 ResNet. ResNet, stands for Residual Networks [17]. It is a traditional neural network used as an integral part of many computer vision functions. Significant success with ResNet has allowed us to train deep neural networks with more than 150layers. It is a deep residual network. More the network is deep, more information can be found, and features are rich. However, tests show that with network depth, the optimization effect has worsened [18], and accuracy was denied. But ResNet can increase the depth of the network as much as possible to get the best result under the condition of ensuring test accuracy [19]. Figure 3 is an architecture of the ResNet50.

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Figure 3. Architecture of ResNet50 [16].

ResNet50 is a CNN with 50 deep layers [16]. A pre-trained version of the trained network with more than a million images forms the ImageNet website. A pre-trained network can split images into 1000 objects. This makes the resultant model well trained [20], and the network has learned to represent the rich features of a variety of images.

4. Implementation

We have used YOLOv5 pretrained model for object detection. To increase the number of images augmentation was done where the options for augmentation were to flip horizontal and rotate by –15 to +15 degrees. The object detection is performed on the extracted frames. The frames are then passed through the model for prediction. Non max suppression function has been used on the predictions to suppress the less likely bounding boxes and keep only the best one. We choose those predictions with the high confidence and suppress all the other predictions that overlap with the selected predictions, greater than a threshold. Then the segregation is done based on the confidence scores, into their respective categories namely, rider_list, head_list, number_list.

To identify if the rider is wearing a helmet or not ResNet50 has been used. We have used a pre-trained model to determine whether or not the rider is wearing a helmet and the classified images are further then passed for number plate recognition. If a helmet is missing on the rider's head, then that frame is further processed for number plate recognition.

At first a person riding a two-wheeler will be detected that is defined in a bounding box. The scope of the search will be limited to the bounding box. The machine will then look inside the box for a helmet. The box is dropped if a helmet is found. The number plate checking subsystem will process the boxes that were retained. The text on the registration plate will be noted after that. For the time and location of any offence a new record will be created which will also keep the snapshot of the bounding box as proof along with the license plate number.

5. Result

This section discusses the experimental achievements of Helmet detection and Number Plate recognition. The experimental evidence has shown that this model has given exceptional results. The weights were taken from a pretrained YOLOv5 and ResNet50 whose accuracy is high.

Case 1. Helmet present

This is the ideal case where the rider along with the passenger (if any) are wearing helmet while riding the two-wheeler. The rider is bounded in a blue box and the head of the rider/s are bounded in green boxes. The output appears as shown:

Figure 4. Rider wearing helmet.

Case 2. Helmet absent

This is the case where a rider is not wearing a helmet or either of the riders are not wearing a helmet. In the figure 5, one of the riders is not wearing a helmet hence it is considered as a rule violation.

Figure 5. Rider is not wearing helmet.

In figure 5, since both the riders are not wearing the helmet, their heads are bounded in red and the number plate of the vehicle is captured.

Case 3. Less confidence

In this case, due to low confidence score, the model is not able to recognize that the rider is wearing a helmet on his head or not. This is represented by yellow coloured bounding box. The confidence score might increase as the image gets bigger and clearer.

Figure 6. Model with less confidence on whether the helmet is present or not.

The result of the presented techniques are good when the density of objects in the focussed area is less. In case of cluster of images the results can further be improved by using multi-focus fusion algorithms [21] that combines two input images to obtain a single higher quality image.

6. Conclusion and Future Work

The paper presents a helmet detection of two-wheeler along with number plate recognition of rule violators based on YOLOv5 algorithm integrated with ResNet50. This model can detect the motorcycle automatically in the input given as a video and detect whether the rider on the two-wheeler is wearing a helmet or not. Our model includes three stages of rider detection, helmet detection, followed by number plate recognition. The proposed model was able to cope up with certain challenges while detecting the riders with and without helmet such as, poor quality of the image, slight changes in angle, brightness, etc. We have learnt about deep learning that considerably aided us in the detection and algorithm for comparing different models.

In future, this model can be extended to automating the cumbersome task of tracking the traffic rule violators such as crossing the red signal, driving a vehicle with speed and to automatically send challan to the respective motorcycle owner. Deep learning techniques can be used to increase accuracy. In addition, it can also be extended to detect whether the vehicle is overloaded by calculating the number of helmets and no helmets. We could extend it to adding a tracking algorithm and recognizean object only once to avoid repeated detection, which is necessary to maintain system efficiently.

References

[1] N. Bhadwal, V. Madaan, P. Agrawal, A. Shukla and A. Kakran, Smart border surveillance system using wireless sensor network and computer vision, In International Conference on Automation, Computational and Technology Management (ICACTM - 2019) (2019), 183-190.

[2] https://morth.nic.in/sites/default/files/Road_Accidents_in_India_2017. pdf Accessed on 24/11/2021.

[3] P. Agrawal, D. Chaudhary, V. Madaan, A. Zabrovskiy, R. Prodan, D. Kimovski and C. Timmerer, Automated bank cheque verification using image processing and deep learning methods, Multimedia Tools and Applications 80(1) (2020), 1-32.

[4] D. Chaudhary, P. Agrawal and V. Madaan, Bank cheque validation using image processing, In International Conference on Advanced Informatics for Computing Research (2019), 148-159.

[5] V. Madaan, A. Roy, C. Gupta, P. Agrawal, A. Sharma, C. Bologa and R. Prodan, XCOVNet: chest X-ray image classification for COVID-19 early detection using convolutional neural networks, New Generation Computing 39(3) (2021), 583-597.

[6] S. Moon, J. Lee, D. Nam, H. Kim and W. Kim, A comparative study on multi-object tracking methods for sports events, 19th International Conference on Advanced Communication Technology (ICACT), Bong-pyeong (2017), 883-885.

[7] K. Dahiya, D. Singh and C. K. Mohan, Automatic detection of bike riders Without helmet using surveillance videos in real-time, Proceeding of International Joint Conference Neural Networks (IJCNN), Vancouver, Canada 24-2 (2016), 3046-3051.

[8] C. C. Chiu, M. Y. Ku and H. T. Chen, Motorcycle detection and tracking system with occlusion segmentation, Proceeding of International Workshop on Image Analysis for Multimedia Interactive Services, Santorini, Greece 6(8) (2017), 32-32.

[9] Z. Tao, F. Shumin, L. Xiaodong and L. Hong, Moving target detection in image sequences, In 2008 27th Chinese Control Conference IEEE (2008), 445-448.

[10] P. Agrawal, R. Kaur, V. Madaan, M. Babu and D. Sethi, Moving object detection and recognition using optical flow and eigenface using low resolution video, Recent Advances in Computer Science and Communications (Formerly: Recent Patents on Computer Science) 13(6) (2020), 1180-1187.

[11] C. Y. Wen, S. H. Chiu, J. J. Liaw and C. P. Lu, The safety helmet detection for ATM's surveillance system via the modified Hough transform, Proceedings of IEEE 37th Annual International Carnahan Conference on Security Technology (2013), 364-369.

[12] Hanit Karwal and Akshay Gordhan, Vehicle number plate detection for Indian vehicles, Proceedings of IEEE Conference on Computational Intelligence and Communication Technology, (2015).

[13] R. V. Silva, T. Aires and V. Rodrigo, Helmet Detection on Motorcyclists Using image descriptors and classifiers, Proceeding of Graphics, Patterns and Images (SIBGRAPI), Rio de Janeiro, Brazil, 27-30 August 2014.

[14] YoloV5 Explained: https://towardsai.net/p/computer-vision/yolo-v5%E2%80%8A-%E2%80%8Aexplained-and-demystified Accessed on 10/12/21

[15] Vishu Madaan, Aditya Roy, Charu Gupta, Prateek Agrawal, Anand Sharma, Christian Bologa and Radu Prodan, XCOVNet: Chest X-ray Image Classification for COVID-19 Early Detection Using Convolutional Neural Networks, New Generation Computing 1-15. DOI: 10.1007/s00354-021 00121-7.

[16] Gurpreet Kaur and Prateek Agrawal, Optimisation of Image Fusion using Feature Matching Based on SIFT and RANSAC, Indian Journal of Science and Technology 9(47) (2016), 1-7.

[17] K. Goel, C. Gupta, R. Rawal, P. Agrawal and V. Madaan, FaD-CODS Fake News Detection on COVID-19 Using Description Logics and Semantic Reasoning International Journal of Information Technology and Web Engineering (IJITWE) 16(3) (2021), 1-20.

[18] P. K. Verma, P. Agrawal, V. Madaan and C. Gupta, UCred: fusion of machine learning and deep learning methods for user credibility on social media. Social Network Analysis and Mining 12(1) (2022), 1-10.

[19] A. Shankhdhar, P. K. Verma, P. Agrawal, V. Madaan and C. Gupta, Quality analysis for reliable complex multiclass neuroscience signal classification via electroencephalography, International Journal of Quality and Reliability Management, (2022).

[20] S. Du, B. Zhang, P. Zhang, P. Xiang and H. Xue, FA-YOLO: An Improved YOLO Model for Infrared Occlusion Object Detection under Confusing Background, Wireless Communications and Mobile Computing, (2021).

[21] Z. Jin, P. Qu, C. Sun, M. Luo, Y. Gui, J. Zhang and H. Liu, DWCA-YOLOv5: An Improve Single Shot Detector for Safety Helmet Detection, Journal of Sensors, (2021).

[22] J. Zhang, S. Chen, S. Tian, W. Gong, G. Cai and Y. Wang, A crowd counting framework combining with crowd location, Journal of advanced transportation, (2021).

[23] A. Shabbir, N. Ali, J. Ahmed, B. Zafar, A. Rasheed, M. Sajid, A. Ahmad and S. H. Dar, Satellite and scene image classification based on transfer learning and fine tuning of ResNet50, Mathematical Problems in Engineering, (2021).

[24] N. Sharma, V. Jain and A. Mishra, An analysis of convolutional neural networks for image classification, Procedia Computer Science 132 (2018), 377-384.

[25] R. U. Khan, X. Zhang, R. Kumar and E. O. Aboagye, Evaluating the performance of ResNet model based on image recognition, In Proceedings of the 2018 International Conference on Computing and Artificial Intelligence (2018, March), 86-90.

[26] G. Kaur and P. Agrawal, Optimisation of image fusion using feature matching based on sift and ransac, Indian Journal of Science and Technology 9(47) (2016), 1-7.

[27] V. Gnanaprakash, N. Kanthimathi and N. Saranya, Automatic number plate recognition using deep learning, In IOP Conference Series: Materials Science and Engineering IOP Publishing, 1084(1) (2021), 012027.