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Automated Catalogue Using Object Detection

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ABSTRACT

The areas of security and wildlife monitoring constantly change, and the use of CCTV surveillance cameras surely has improved our ability to protect a range of environments. However, innovative methods are needed to address the persistent challenge of efficiently examining large quantities of video in cases of theft or animal contact. This study presents a new "Automated Catalogue System using Object Detection," which makes use of innovative technologies like Single Shot Multibox Detector (SSD), OpenCV, and MobileNetV3. The system catalogs objects that are identified and operates in real time using a camera. It logs critical data, such as the name of the detected object's category, the time, date, and confidence level. In addition to increasing security measures, this project addresses wildlife-associated problems in an innovative manner, providing a solution for situations where wild animals break into human settlements. The project uses an automatic categorization approach to take photographs and record them, then uses a user-friendly web application to provide an accessible record. This comprehensive strategy removes uncertainty regarding animal encounters and provides communities with a dependable tool for wildlife monitoring and awareness. Because it combines accurate categorization, image capturing, and real-time object detection, this initiative is a major contribution to technical progress. This flexible device can be used for both managing animals and security surveillance.

Keywords – **Catalogues, CCTV, MobileNetV3, OpenCV, Single Shot Multibox Detector**

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1. INTRODUCTION

The wide employment of CCTV surveillance cameras in contemporary security and wildlife monitoring scenarios has surely improved the capacity to view and protect a variety of habitats. However, a significant challenge arises when incidents of theft or other unusual occurrences demand scrutiny of extensive footage, leading to time wastage and inefficiency. Our project's goal is to address this problem by utilizing real-time object detection through a CCTV to develop an automatic cataloging system that will change surveillance approaches. Utilizing the MobileNetV3 [3], the system applies the Single Shot Detection (SSD) [9] method. The initiative's objectives include Firstly, it aims to precisely identify and classify in real-time anything that comes into view of the webcam, including people, animals, and cars. Second, in the case that an object is detected as a person or an animal with a confidence level more than 70%, the system captures and stores real-time photographs in a database. These photos also include information about the kind of object found, the level of confidence, the date, and the time of detection. It is no longer necessary to watch the entire movie because of this data, which makes it possible to fast and simply access particular occurrences. The system uses Python for program development, OpenCV as the framework, ReactJS for the web application interface, and Firebase as the database.

Our work enhances the use of security monitoring to address wildlife-related challenges, particularly in areas near forests, while also improving the monitoring itself. The arrival of wild animals in villages typically causes confusion and fear in people who live there. Using our automated cataloging system, the computer can recognize and photograph these species, and it will make the records accessible through the web application. This not only eliminates all questions but also provides communities with an effective tool for monitoring and raising awareness of animals. Because our project combines real-time item detection, image capture, and thorough categorization, it is positioned as a beneficial solution with applications in security surveillance and wildlife management.

2. LITERATURE REVIEW

Jisoo Jeong, Hyojin Park, and Nojun Kwak present a novel approach to enhance the accuracy of the Single Shot

Multibox Detector (SSD) in object detection. The proposed network exhibits superior results on the Pascal VOC 2007 test set, achieving 78.5% mean average precision at 35.0 FPS with a 300 x 300 input size. This outperforms conventional SSD, YOLO, Faster-RCNN, and RFCN, establishing a state-of-the-art mAP while maintaining faster speeds than Faster-RCNN and RFCN, showcasing its effectiveness in object detection [1].

Reagan R. Galvez, Argel A. Bandala, Elmer P. Dadios, Ryan Rhay P. Vicerra, and Jose Martin Z. Maningo explore the pivotal role of vision systems in mobile robotics for tasks like navigation, surveillance, and explosive ordnance disposal. A comparative analysis between the Single Shot Multi-Box Detector (SSD) with MobileNetV1 and Faster Region-based Convolutional Neural Network (Faster-RCNN) with InceptionV2 reveals a trade-off: one model excels in real-time applications due to speed, while the other provides more accurate object detection, offering valuable insights for diverse mobile robot applications [2].

Ayesha Younis, Li Shixin, Shelembi Jn, and Zhang Hai present a compelling paper on object identification, leveraging MobileNet within the Single Shot Multi-Box Detector (SSD) framework. The proposed algorithm demonstrates real-time detection, specifically applied to webcam feeds for video stream object identification. By integrating MobileNet and SSD, the research emphasizes a swift and efficient deep learning-based approach to object detection. This research enhances accuracy for real-time detection, addressing the requirements of daily monitoring in indoor and outdoor environments [3].

Sheping Zhai, Dingrong Shang, Shuhuan Wang, and Susu Dong propose a novel improvement to the Single Shot Multibox Detector (SSD) for object detection, introducing DF-SSD based on Dense Convolutional Network (DenseNet) and feature fusion. DF-SSD achieves notable results, outperforming SSD on PASCAL VOC 2007 by 3.1% mAP with reduced parameter requirements, showcasing its advanced detection capabilities for small objects and those with specific relationships [4].

Sheping Zhai, Dingrong Shang, Shuhuan Wang, and Susu Dong present SSD-MSN, an advanced multi-scale object detection network derived from the Single Shot Multibox Detector (SSD). Introducing a valid dividing image strategy further enhances performance through data augmentation, generating 3x3 clipped areas. Experimental results on PASCAL VOC and COCO datasets showcase SSD-MSN's state-of-the-art detection capabilities, particularly in improving multi-scale object detection, demonstrating its effectiveness in complex scenarios [5].

In their recent work, Abhinav Juneja, Sapna Juneja, Aparna Soneja, and Sourav Jain contribute to the evolving field of object detection, focusing on real-time applications. Utilizing the ssd_v2_inception_coco model, their proposed Single Shot Detection (SSD) approach exhibits substantial improvements in accuracy. This model not only detects numerous objects simultaneously but also demonstrates significant accuracy enhancements over established methodologies, making it a valuable asset for applications such as parking lots, human identification, and inventory management [6].

Md Alamin Feroz, Marjia Sultana, Md Rakib Hasan, Aditi Sarker, Partha Chakraborty, and Tanupriya Choudhury address the challenging task of real-time object detection and recognition in uncontrolled environments. Their research introduces an improved technique using Single Shot Detector (SSD) and You Only Look Once (YOLO) models, exhibiting promising results. Utilizing Convolutional Neural Networks (CNN), the proposed technique achieves real-time performance with satisfactory detection and classification results, offering enhanced accuracy. The investigated model attains an impressive accuracy range of 63–90% in object detection and classification, showcasing its effectiveness in challenging environments [7].

Qianjun Shuai and Xingwen Wu introduce enhancements to the Single Shot Multi Box Detector (SSD), a prominent deep learning-based object detection algorithm. Incorporating Batch Normalization (Batch Norm) operations into the network aims to enhance generalization and accelerate training. The paper extends SSD's capabilities to include object counting in image recognition. Users can interact with the system on the front-end page, selecting data for real-time detection, and viewing results, including object types and counts, contributing to improved accuracy and efficiency in object detection [8].

Xin Lu, Xin Kang, Shun Nishide, and Fuji Ren address challenges in object detection and recognition, especially for small and diverse datasets of dangerous goods. They propose an innovative approach by integrating the Single Shot Multi-Box Detector (SSD) with a ResNet101 network, aiming to enhance the learning efficiency and accuracy. The proposed model surpasses other neural networks, showcasing improved performance in learning efficiency and accuracy, particularly beneficial for applications involving small and diverse datasets of hazardous materials [9].

Kanishk Wadhwa and Jay Kumar Behera delve into the realm of object detection, focusing on Real-Time Object Detection using the Single Shot Detector (SSD) algorithm. The paper aims to analyze and implement SSD for real time object detection, showcasing its speed and accuracy, ultimately contributing to the evolving knowledge in this domain [10].

G Chandan, Ayush Jain, and Harsh Jain underscore the transformative impact of deep learning in the realm of Artificial Intelligence. The paper advocates the synergistic fusion of SSD and Mobile Nets, ensuring efficient object detection and tracking without compromising performance. This amalgamation contributes to the ongoing advancements in the field of deep learning-based object detection [11].

Qunjie Yin, Wenzhu Yang, Mengying Ran, and Sile Wang present an innovative solution to the challenge of detecting small objects in computer vision with their proposed method, Feature Fusion and Dilated Convolution-based Single Shot multi-box Detector (FD-SSD). Utilizing VGG-16 as the backbone network, the model incorporates a multi-layer feature fusion module and a multi-branch residual dilated convolution module. Experimental results on PASCAL VOC2007 and MS COCO datasets showcase

FD-SSD's effectiveness, achieving significant improvements in small object detection [12].

Dr. S. V. Viraktamath, Ambika Neelopant, and Pratiksha Navalgi delve into the realm of object recognition within computer vision, a pivotal advancement facilitating the identification and localization of entities in digital images and videos. The paper comprehensively surveys various algorithms, quality metrics, speed-size trade-offs, and training approaches. Focusing on the You Only Look Once (YOLO) and Single Shot Multi-Box Detector (SSD) for single-step detection, as well as the Faster R-CNN for two-step detection, the study provides a holistic exploration of object recognition and its applications [13].

Hyeong-Ju Kang introduces a Convolutional Neural Network (CNN) accelerator designed for real-time object detection, addressing the challenge of high computational requirements. Employing a single-shot multibox detector (SSD) with VGG16, the CNN accelerator implements a pruning scheme to reduce weight storage. The proposed design achieves a remarkable 42 frames per second (FPS) on the XC7VX690T FPGA, showcasing a VOC07 test mean Average Precision (mAP) of 78.13% [14].

Mohit Phadtare, Varad Choudhari, Rushal Pedram, and Sohan Vartak explore the challenges of object recognition in aerial surveillance using camera-equipped drones. The paper delves into a comparative analysis of systematic approaches for detecting vehicles, people, and animals in images and real-time monitoring. Emphasizing the significance of precision, the research contributes valuable insights into object detection methodologies, particularly in the context of aerial surveillance, where robust performance is essential for reliable results [15].

Shuren Zhou and Jia Qiu introduce an improved Single Shot Multibox Detector (SSD) method, termed MA-SSD, addressing limitations in quickly recognizing significant object areas in images. MA-SSD incorporates an attention mechanism to generate multi-scale attention features, enhancing the feature representation capability and boosting detection accuracy. Demonstrating competitive performance on the PascalVOC dataset, MA-SSD offers an innovative approach to refining object detection through interactive multi-scale attention features within the SSD framework [16].

In the study by Tiagrajah V. Janahiraman and Mohamed Shahrul Mohamed Subuhan, traditional machine learning methods for traffic light detection are replaced by advanced deep learning techniques. This research demonstrates the effectiveness of deep learning, particularly Faster-RCNN, in robustly detecting traffic lights and highlights the potential for real-time applications in traffic management [17].

The article by Zhe Huang, Zhenyu Yin, Yue Ma, Chao Fan, and Anying Chai addresses the challenge of low accuracy in detecting small objects in mobile phone component images. They introduce an improved SSD algorithm, CSP-SSD (Cross Stage Partial SSD), which enhances the network structure using gradient flow information, deconvolution, and multi-scale transformation. The proposed CSP-SSD algorithm demonstrates high accuracy, particularly for small objects, addressing robustness concerns in mobile phone component image detection [18].

The paper by Khusni, U., Arymurthy, A.M., Susanto, H. focuses on the critical challenges in traditional object detection methods, emphasizing the limitations in accurately detecting small objects with varied backgrounds. This modification aims to address the accuracy issues associated with small object detection. Experimental results demonstrate improved accuracy, with SSD (ResNeXt101) achieving 67.17%, surpassing the previous SSD framework with ResNet101, which had an accuracy of 66.09%. The study contributes valuable insights for enhancing object detection in real-world scenarios [19].

The proposed model by Shridhar. H, Sumalata M. V, Thushara M, Ashwini D. N, M. Suma, R. Premananda, Sunil S. Harakannanavar is focused on achieving high accuracy and real-time performance in object detection using a deep learning-based approach. The two types of state-of-the-art methods for object detection were discussed: one stage methods prioritizing inference speed, such as YOLO, SSD, and RetinaNet, and two-stage methods prioritizing detection accuracy, such as Faster R-CNN, Mask R-CNN, and Cascade R-CNN. The Faster R-CNN and SSD have better accuracy, while YOLO performs better when speed is given preference over accuracy. The proposed model uses a deep learning-based approach that combines SSD and MobileNet to efficiently implement detection and tracking. The SSD eliminates the feature resampling stage and combines all calculated results as a single component, while MobileNetV2 is a lightweight network model that uses depth-wise separable convolution to perform efficient object detection without compromising on performance. The model aims to elaborate on the accuracy of the SSD object detection method and the importance of the pre-trained deep learning model MobileNetV2. The experiments were conducted on the COCO dataset to recognize objects, and the model was also tested on real-time images for object recognition. The resulting system is fast and accurate, making it suitable for applications that require object detection [20].

3. METHODOLOGY

The Single Shot Multibox Detector (SSD) model and the OpenCV framework's capabilities are explored in this real-time object detection project's suggested methodology. Setting up the webcam to record live video frames using the CV2 library is the first step in the project. After that, the system loads the chosen SSD model and configures it with crucial settings like input size, scale, mean, and color shifting. For model training, we used the COCO[21] dataset in this case. Class names are loaded from the coco names file to help with object identification. Every video frame is processed by the system using the SSD model, and in order to improve the object detections, a confidence threshold is applied. Crucially, our approach includes a variation on image capture by employing the OS library to save only photographs of observed people or animals. In line with the project's general goals, the resultant system is to make a significant contribution to security-related applications, monitoring, and supporting subsequent clarifications. Figure 1 shows the proposed system's architecture.

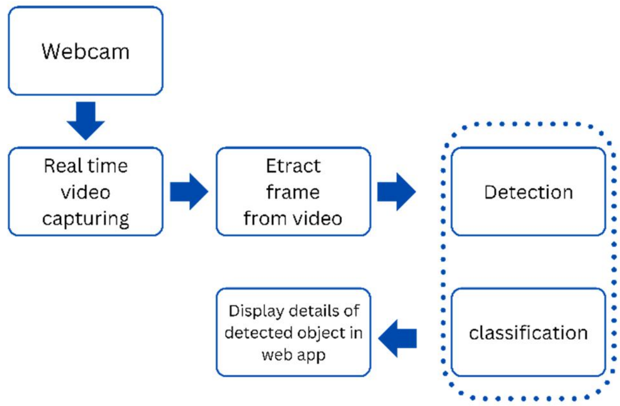

Fig. 1. Proposed System Architecture Diagram

3.1 Single Shot Multibox Detectors(SSDs)

A Single Shot Detector (SSD) is an innovative object detection algorithm in computer vision. Its capacity to quickly and precisely identify and locate items within picture or video frames makes it stand out. SSD is unique in that it can achieve this in a single pass of deep neural network, which makes it incredibly effective and perfect for real-time applications. SSD does this by using numerous anchor boxes in feature maps at different aspect ratios. It can successfully manage objects of various sizes and forms owing to these anchor boxes. Additionally, SSD makes use of multi-scale feature maps to identify items at different scales, guaranteeing precise identification of both big and small things in the picture. SSD is a useful tool for jobs involving several item categories in a single image because of its ability to recognize multiple object classes at once. The SSD architecture is shown in Figure 2 below.

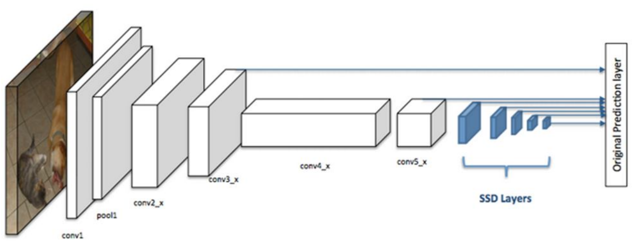

Fig 2. SSDs Architecture.

3.2 MobileNet

MobileNet is a CNN architecture model for Image Classification and Mobile Vision. While there are other models as well, MobileNet stands out due to its extremely low processing power requirements for transfer learning applications. Because of this, it works perfectly with mobile devices, embedded systems, and PCs with low computing efficiency or no GPU, all without significantly sacrificing the accuracy of the output.

3.2.1 MobileNetV3

A more intelligent and efficient method of creating neural networks for applications such as image recognition is MobileNetV3. Without requiring human input, MobileNetV3 use AutoML, a form of autonomous learning, to determine the optimal network architecture. It use a combination of MnasNet and NetAdapt algorithms to determine an approximate design and then optimize it for optimal performance. The inclusion of "squeeze-and-excitation" blocks in the basic architecture of MobileNetV3 is one of its features. These blocks concentrate on the most crucial components while disregarding less significant aspects, which helps the network acquire higher-quality information. The coco dataset was used to train this model. This improves the network's ability to comprehend and identify items. Figure 3 displays the MobileNetV3 block below.

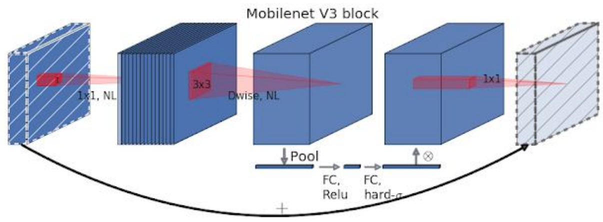

Fig 3. Block of MobileNetV3

The way that MobileNetV3 optimizes some of the complex components of its design is another smart feature. This eliminates three complex layers without compromising accuracy, increasing network speed. In experiments, MobileNetV3 has demonstrated a 25% reduction in object recognition time compared to its previous iterations, all while maintaining the same degree of accuracy. A more clever and economical method of creating neural networks for tasks like object recognition in photos is called MobileNetV3. To make the network faster and more intelligent, it makes use of optimizations, automated learning, and smart design decisions.

3.3 Firebase

Google Firebase acts as a one-stop solution for developers, providing a unified platform to handle critical aspects of app development, from user authentication to real-time data management and performance monitoring. With Firebase, developers can enhance user experiences, expedite workflows, and ensure the reliability of their mobile applications. The view of data in database is given below in Figure 4 and Figure 5.

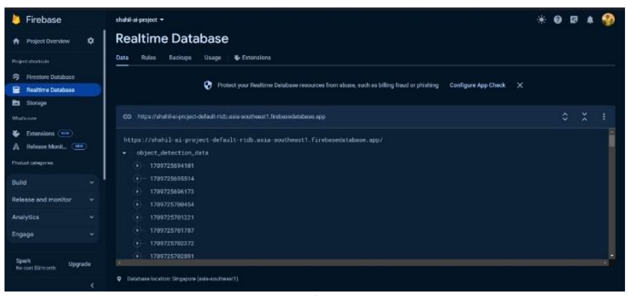

Fig 4. Storing of data in Firebase.

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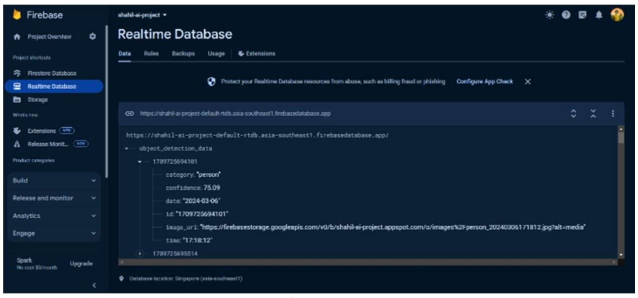

Fig 5. Details of each data in Firebase

3.4 User Interface

In this project we provide a simplest user-friendly interface, user to access the details of detected objects. And UI is build using React. Users can access data via the user interface by filtering by category, date, time, or confidence level. If necessary, users may also hide any column and view example photographs. The data view in the web application is displayed in Figures 6, 7, 8, and 9 below.

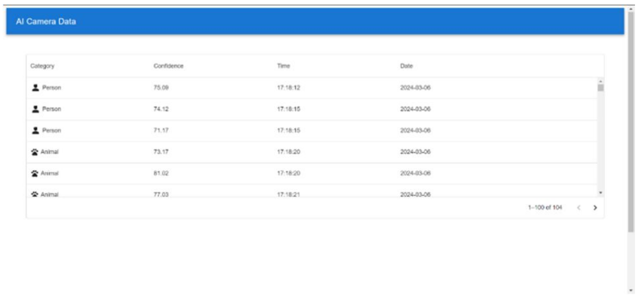

Fig 6. View of data in Web app

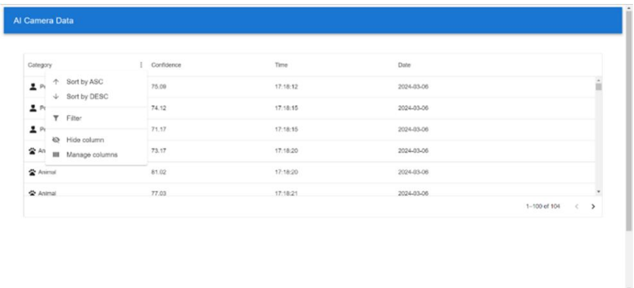

Fig 7. Filtering option of the data in table.

The app shows the details including image of the detected object, category name of the object, confidence level of the detection, date of the detection and time of the detection. The take the data lively.

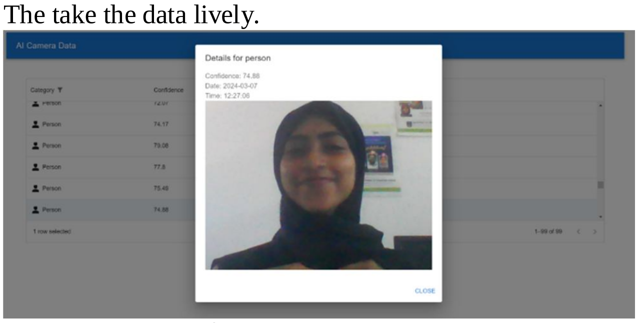

Fig 8. View of detected Person details in Web app.

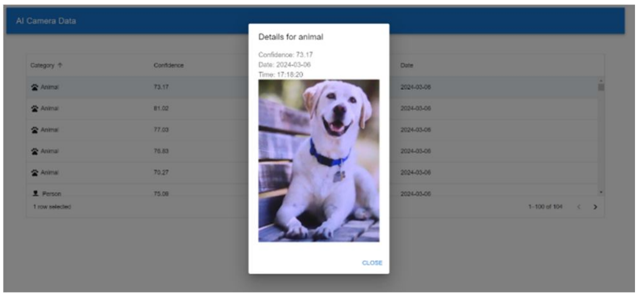

Fig 9. View of detected Animal details in Web app.

4. EXPERIMENTAL RESULT

The integration of SSD, MobileNetV3, OpenCV, ReactJS, Webcam produced interesting outcomes:

4.1 Object Detection

Single Shot Detection (SSD) provides highly fast and accurate object detection. Using the Coco dataset, we had trained it. Over 328,000 photos were annotated into 91 classes [21]. It finds the object equally fast. It rapidly and accurately captures the detected object. and without fail sends the information to the firebase. The anchor boxes have proper bounds. Using a machine with GPU support will improve object detection. Figures 10 and 11 show the object detection using camera.

Fig 10. Detection of a person from the live footage

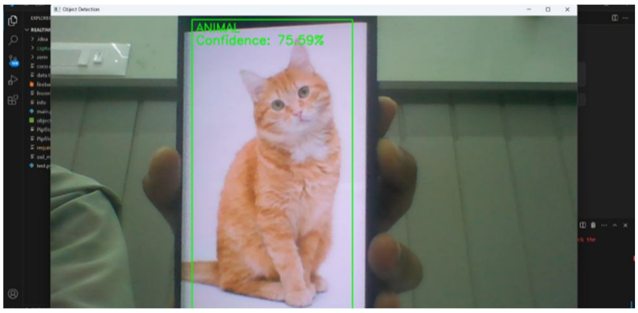

Fig 11. Detection of Animal from live footage

4.2 Camera Accuracy

In Our project we have used normal laptop Webcam as camera for detecting object in real time. Comparatively the captured images of the detected object is low quality due to this normal camera of the laptop. But we have got maximum good results that a laptop webcam can do with. If we use a good camera for capturing of the video surveillance it can attain a good result.

4.3 Confidence Score

The confidence score in object detection represents the algorithm's certainty that a detected object accurately corresponds to a particular class. As represented as a probability, it represents the degree of confidence in the identified class, assisting in the process of making decisions and filtering out false positives in object recognition algorithms. The camera and object detection model's accuracy determine the confidence score.

4.3.1 Average confidence of person

Sample images of the detection of different person with their confidence score has given below in Figure 12.

Fig 12. Sample images of detection of person with confidence

Total confidence score = 69.71 + 70.35 + 71.27 + 70.01 + 74.53 + 66.82 + 69.46 + 69.77 = 561.92

No of detection = 8

Average confidence = Total confidence score/No of detection = 561.92/8 = 70.24

4.3.2 Average confidence of animal

Sample images of the detection of different animals with their confidence score has given below in Figure 13.

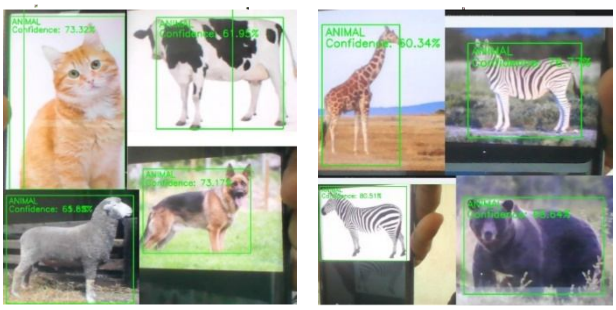

Fig 13. Sample images of detection of different animals with confidence

Total confidence score = 73.32 + 61.95 + 65.68 + 73.17 + 60.34 + 76.77 + 80.51 + 68.64 = 594.04

No of detection = 8

Average confidence = Total confidence score/No of detection = 594.04/8 = 74.255

5. Discussion

Since the system we utilized for this project was poorly designed, we were unable to apply extremely precise algorithms like YOLO V8. Additionally, we employed a standard laptop camera, which has a low resolution and reduces the quality of the photographs it takes of the thing it detects. It reduces the confidence of the detection as well as the clarity of the image. Our project's low-spec processors and camera make it extremely difficult to employ new algorithms, which also somewhat reduces the accuracy of our work. A camera with a fast shutter speed and resolution, along with a computer equipped with a GPU that supports cuda graphics, are essential for achieving superior accuracy when localizing the project. The performance of the embedded system software will increase if we use the Jetson Nano developer kit.

6. Conclusion

In conclusion, our project presents an innovative approach to wildlife monitoring and security surveillance through the use of a real-time object detection system. Using the use of the MobileNetV3-powered Single Shot Detection (SSD) algorithm, the system demonstrates rapid and accurate object detection for people, animals, and vehicles. The integration of Firebase, ReactJS, and OpenCV enhances the project's capabilities. This allows for the effective cataloging and storing of essential characteristics such as timestamp, confidence level, and item kind. It is easy to obtain the categorized data thanks to the user-friendly interface, which reduces the need to sift through a large amount of video content and expedites event retrieval.

Our tests verify that the system can achieve good object detection accuracy even with a standard laptop webcam. The combination of SSD, MobileNetV3, and OpenCV ensures quick and precise item detection, and the corresponding confidence scores provide helpful information about the system's level of assurance. Even if the project functions fine with a regular webcam, it could be worthwhile to look into better cameras in order to potentially enhance image capturing and system performance in general. The average confidence scores that are regularly obtained for both animal and person detection demonstrate the reliability of the technology. In security and wildlife management contexts, this confirms the system's reputation as a powerful tool for complete cataloguing and real-time object detection.

7. Reference

[1] Jisoo Jeong, Hyojin Park, Nojun Kwak., *"Enhancement of SSD by concatenating feature maps for object detection."*, arXiv preprint arXiv:1705.09587, 2017 DOI: 10.5244/C.31.76

[2] Reagan L Galvez, Argel A Bandala, Elmer P Dadios, Ryan Rhay P Vicerra, Jose Martin Z Maningo *"Object detection using convolutional neural networks"* TENCON 2018-2018 IEEE Region 10 Conference, 2023-2027, 2018
DOI: 10.1109/TENCON.2018.8650517

[3] Ayesha Younis, Li Shixin, Shelembi Jn, Zhang Hai *"Real-time object detection using pre-trained deep learning models MobileNet-SSD"* Proceedings of 2020 the 6th international conference on computing and data engineering, 44-48, 2020
DOI: 10.1145/3379247.3379264

[4] Sheping Zhai, Dingrong Shang, Shuhuan Wang, Susu Dong DF-SSD: *"An improved SSD object detection*

algorithm based on DenseNet and feature fusion" IEEE access 8, 24344-24357, 2020
DOI: 10.1109/ACCESS.2020.2971026

[5] Zuge Chen, Kehe Wu, Yuanbo Li, Minjian Wang, Wei Li SSD-MSN: *"An improved multi-scale object detection network based on SSD"* IEEE Access 7, 80622-80632, 2019
DOI: 10.1109/ACCESS.2019.2923016

[6] Abhinav Juneja, Sapna Juneja, Aparna Soneja, Sourav Jain *"Real time object detection using CNN based single shot detector model"* Journal of Information Technology Management 13 (1), 62-80, 2021
DOI: 10.22059/JITM.2021.80025

[7] Md Alamin Feroz, Marjia Sultana, Md Rakib Hasan, Aditi Sarker, Partha Chakraborty, Tanupriya Choudhury *"Object detection and classification from a real-time video using SSD and YOLO models"* Computational Intelligence in Pattern Recognition: Proceedings of CIPR 2021, 37-47, 2022
DOI: 10.1007/978-981-16-2543-5_4

[8] Qianjun Shuai, Xingwen Wu *"Object detection system based on SSD algorithm"* 2020 international conference on culture-oriented science & technology (ICCST), 141-144, 2020
DOI: 10.1109/ICCST50977.2020.00033

[9] Xin Lu, Xin Kang, Shun Nishide, Fuji Ren *"Object detection based on SSD-ResNet"* 2019 IEEE 6th International Conference on Cloud Computing and Intelligence Systems (CCIS), 89-92, 2019
DOI: 10.1109/CCIS48116.2019.9073753

[10] Kanishk Wadhwa, Jay Kumar Behera *"Accurate real-time object detection using SSD"* International Research Journal of Engineering and Technology (IRJET) 7 (05), 2395-0072, 2020
https://www.irjet.net/archives/V7/i5/IRJET-V7I5504.pdf

[11] G Chandan, Ayush Jain, Harsh Jain *"Real time object detection and tracking using Deep Learning and OpenCV"* 2018 International Conference on inventive research in computing applications (ICIRCA), 1305-1308, 2018
DOI: 10.1109/ICIRCA.2018.8597266

[12] Qunjie Yin, Wenzhu Yang, Mengying Ran, Sile Wang *"FD-SSD: An improved SSD object detection algorithm based on feature fusion and dilated convolution"* Machine Vision Engineering Research Center, Hebei University, Baoding 071002, China
DOI: 10.1016/j.image.2021.116402

[13] Dr. S. V. Viraktamath,Ambika Neelopant,Pratiksha Navalgi *"Comparison of YOLOv3 and SSD Algorithms"* International Journal of Engineering Research & Technology (IJERT) ISSN: 2278-0181
DOI: 10.17577/IJERTV10IS020077

[14] Hyeong-Ju Kang *"Real-Time Object Detection on 640x480 Image With VGG16+SSD"* 2019 International Conference on Field-Programmable Technology (ICFPT)
DOI: 10.1109/ICFPT47387.2019.00082

[15] Shuren Zhou, Jia Qiu, *"Enhanced SSD with interactive multi-scale attention features for object detection"* Multimed Tools Appl 80, 11539–11556 (2021).
DOI: 10.1007/s11042-020-10191-2

[16] Mohit Phadtare, Varad Choudhari, Rushal Pedram, Sohan Vartak *"Comparison between YOLO and SSD Mobile Net for Object Detection in a Surveillance Drone"*. International journal of scientific research in engineering and management 2021
DOI: 10.13140/RG.2.2.34029.51688

[17] Tiagrajah V. Janahiraman; Mohamed Shahrul Mohamed Subuhan. *"Traffic Light Detection Using Tensorflow Object Detection Framework"* 2019 IEEE 9th International Conference on System Engineering and Technology (ICSET)
DOI: 10.1109/ICSEngT.2019.8906486

[18] Zhe Huang, Zhenyu Yin, Yue Ma, Chao Fan, Anying Chai. *"Mobile phone component object detection algorithm based on improved SSD"* Shenyang Institute of Computing Technology, Chinese Academy of Sciences, Shenyang 110168, China, University of Chinese Academy of Sciences, Beijing 100049, China
DOI: 10.1016/J.PROCS.2021.02.037

[19] Khusni, U., Arymurthy, A.M., Susanto, H. (2022). *"Small Object Detection Based on SSD-ResNeXt101"*. In: Mahyuddin, N.M., Mat Noor, N.R., Mat Sakim, H.A. (eds) Proceedings of the 11th International Conference on Robotics, Vision, Signal Processing and Power Applications. Lecture Notes in Electrical Engineering, vol 829. Springer, Singapore.
DOI: 10.1007/978-981-16-8129-5_162

[20] Shridhar H., Sumalata M. V., Thushara M., Ashwini D. N., M. Suma, R. Premananda, Sunil S. Harakannanavar *"Development of Object Recognition Model Using Machine Learning Algorithms on MobileNet V2"* International Journal of Advanced Networking and Applications (IJANA) in 2023
DOI: 10.35444/ijana.2023.15210

[21] Tsung-Yi Lin, M. Maire, Serge J. Belongie, James Hays, P. Perona, Deva Ramanan, Piotr Dollár, C. L. Zitnick *"Microsoft COCO: Common Objects in Context"* European Conference on Computer Vision 2014.
DOI: 10.1007/978-3-319-10602-1_48