East Journal of Engineering
ISSN: 3079-9376
Volume 1 , Issue 5
Publisher: East Publication & Technology
DOI: https://doi.org/10.63496/eje.Vol1.Iss5.232

Cow Crossing Road Detection with Yolov8 and SSD

***Mohammed Alawaid* *[1], *Nasser Al Musalhi* [2]**

[1] Department of Computer Engineering, Cyprus International University, Nicosia, North Cyprus, Mersin 99258.
[2] Faculty of Computer Studies, Arab Open University, Muscat, Oman.
*Corresponding Author Email: mohdalawaied@yahoo.com

Received: 20/11/2025, **Revised**: 01/12/2025, **Accepted**: 04/12/2025, **Published**: 06/12/2025

***Abstract*:**

The increase in car accidents involving stray cows on Oman's roadways has become a pressing concern, resulting in a substantial rise in fatalities and injuries. This study aims to compare the accuracy of two prominent object detection algorithms, YOLO v8 and SSD, in detecting cows crossing roads under various weather conditions in Oman's Dhofar region to improve road safety and provide valuable insights for road monitoring authorities. The methodology involves the creation of a dataset comprising 15 videos capturing cow crossings under different weather conditions. The study evaluates detection accuracy at different confidence levels (25%, 50%, 75%, and 90%) and collects results in terms of true positives (TP), false positives (FP), and false negatives (FN). The experimental results reveal that YOLO v8 consistently outperforms SSD in all weather conditions. In clear daytime weather, YOLO v8 achieves an average precision of 96%, while SSD achieves 59%. In foggy conditions, YOLO v8 maintains a precision of 64% compared to SSD's 18%. In nighttime scenarios, YOLO v8 excels with a precision of 94%, while SSD lags at 5%. Overall, YOLO v8 attains an impressive mean average precision of 84.67% across all conditions, while SSD achieves 27.33%. These findings underscore the significance of selecting the right object detection model for specific weather conditions to enhance road safety.

***Keywords*: Cow Crossing Road, Object Classification, Object Detection, Object Tracking, SSD, YOLO.**

1. Introduction

There has been a notable rise in the incidence of car accidents involving stray cows in Oman. Based on data provided by the National Centre for Statistics and Information (NCSI), it was observed that there was a 17% rise in the number of fatalities and injuries resulting from collisions with cattle on Oman's roadways in the previous year. Specifically, 11 individuals lost their lives, while 45 individuals sustained injuries. The southern area of Dhofar in the Sultanate has reported the highest number of accidents in 2021, with a total of 21 events. [1]. The Dhofar government in the Sultanate of Oman encompasses a vast mountainous area that is home to a significant population. This region is distinguished by its verdant oasis, which provide appropriate grazing grounds for cattle. Notably, the inhabitants of this area possess approximately 60% of the livestock found within the Sultanate of Oman[1]. The road infrastructure traverses a series of consecutive mountain ranges, exhibiting winding paths, yet they are meticulously surfaced and possess aesthetically pleasing attributes. However, the aesthetic appeal diminishes as fog and darkness descend, particularly when cows intentionally traverse and rest upon these roads, resulting in numerous fatalities caused by traffic collisions. Based on the statistical data provided by the Royal Oman Police, it can be observed that the frequency of accidents in these specific places exceeds 200 incidents annually. In recent times, specifically in the year 2022, a series of unfortunate incidents resulted in the unfortunate demise of over sixty individuals[2]

The rise in automobile accidents resulting from collisions with animals signifies a significant toll on human lives, with a substantial number of injuries and fatalities. This phenomenon can be attributed to limited sight in certain road settings, including hills, slopes, and road bends, where the presence of cows crossing the road is more likely. The driver's ability to anticipate objects or obstacles may be hindered due to reduced sight when operating the vehicle. Simultaneously, the presence of foggy weather and darkness during nighttime might amplify the level of risk and the likelihood of accidents occurring. According to police data, a significant proportion of accidents can be attributed to collisions with cows during road crossings. Given that the owners of these cows do not refrain from allowing them to graze and traverse through streets, it becomes imperative for technology to play a role in addressing this issue[3].

This study aims to compare the accuracy of a pretrained model of YOLO v8 algorithm (Ultralytics YOLOv8) against (MobileNet SSD) model for cow detection while crossing road in three different weather situations: day clear weather, foggy weather, and night mode. Both YOLOv8 and SSD are capable of doing real-time object detection, each with distinct advantages and disadvantages. The selection between these options is contingent upon various aspects, including the precise demands of the application, the trade-offs between velocity and precision, and the computational resources that are accessible[3][4].

The novelty of this study is to evaluate the performance of two state-of-the-art object detection algorithms as a case study of cow crossing road detection in Dhofar region; YOLOv8 and SSD, under different vision conditions, including normal day weather, foggy weather, and night mode.

1.1 Research Contribution

This study, we have made a significant contribution to the field of computer vision and livestock management by conducting an extensive study on the detection of cows crossing roads in natural video footage captured in the region of Dhofar, located in the south of Oman. Our primary focus was to evaluate the performance of two state-of-the-art object detection algorithms, YOLOv8 and SSD, under challenging weather conditions, including normal day weather, foggy weather, and night mode.

Through meticulous experimentation and analysis, we have not only demonstrated the feasibility of automating the detection of cows in a real-world context but have also provided valuable insights into the strengths and weaknesses of YOLOv8 and SSD in these scenarios. Our findings offer practical implications for improving road safety in regions with a significant presence of livestock and varying weather conditions.

Furthermore, this research contributes to the broader discussion on the applicability of computer vision techniques in agriculture and animal protection, addressing a crucial issue in the Dhofar region and potentially serving as a model for similar environments worldwide. Our comprehensive evaluation and comparative analysis of these algorithms in diverse weather conditions provide a foundation for future developments in autonomous livestock management systems and transportation safety.

2. Literature Review

Target detection and cow standing behavior recognition based on YOLOv5 algorithm, 2022, by Xin Tian, Bomeng L, and others. YOLOv5 model implementation is assessed and studied for environment modeling and target detection algorithm objectives. The results of the experiments demonstrate that the experimental detection correctness accuracy is 97.6% and the preprocessing time in detecting a single image is It can swiftly and accurately recognize cows' standing activity, laying the groundwork for the identification and localization of cows' basic behavior [5]. Another study titled Design and Implementation of Human Detection Feature on Surveillance Embedded IP Camera, 2018, by Widodo Setyo Yuwono et al. Less illumination or an obstruction like a person's face that faces away from the camera's lens cause the master function to be unable to detect objects. The night vision function is also discussed in this study for the surveillance camera prototyping in order to reduce the detection failure. To reduce the likelihood of failure, human object detection using the Head and Shoulders approach as a slave feature is still in place. The suggested approach functions properly, especially when it combines the Head and Shoulders method with Face Detection. Utilizing the night vision capability also increases the accuracy for detecting object movement by more than 80% under various lighting conditions [6]. Another study, titled "A Dim-small Target Real-time Detection Method Based on Enhanced YOLO," was carried out in the year 2022 by Mingyang Yan and colleagues. A pre-processing technique is recommended in this study for the purpose of increasing feature variety and invariance, as well as enhancing the performance of the YOLO model when it comes to dealing with dim-small targets. This recommendation was made because of the findings of this investigation. The findings of the experiments show that the recommended technique works better than the original Yolo methodology when it comes to detection accuracy and resilience in remote sensing target identification. The experiments were designed to determine which way would perform better. This strategy, although being able to retain real-time capability in an environment with a minimum configuration for the hardware, is valuable for spreading knowledge about the algorithm as well as using the algorithm itself. However, it is not quite as good as it might be, and as a consequence, a data augmentation approach based on the YOLOv4 model was implemented in order to improve the performance and provide favorable results, particularly in situations in which the number of sensitive target data is limited. According to our method of augmentation, the AP rate is even capable of reaching 99% in certain photo categories that contain images with simple backgrounds and components that are clearly visible, such as airplanes[13]. Another piece of research is titled "An Algorithm for Obstacle Detection based on YOLO and Light Field Camera," and it was written by Rumin Zhang and five other researchers. This research demonstrates a novel approach to the identification of obstacles found inside buildings. The YOLO object detection method and the light field camera, which is easier to use than a normal RGB-D sensor and can record both a depth picture and a high-resolution image simultaneously in a single exposure, are merged in the algorithm. This results in the camera being able to catch both in a single exposure. As input, the RGB picture that was created by the light field camera is sent to the YOLO model, which was trained using more than one hundred different categories of everyday objects. The size of the obstruction as well as its specific placement were precisely determined by the computer using the depth map and the object data. According to the findings of the experiments, the suggested approach has the potential to deliver increased detection accuracy when used in an indoor setting[14].

3. Methodology

This section provides a description of the experimental setup utilized in our test scenario, the dataset that was recorded, the object detection methods employed, and the evaluation criteria that were utilized. In this discussion, we will examine the utilization of two trained algorithms to analyze and classify various weather circumstances, including regular day weather conditions, fog weather, and night mode[24], [25].

3.1 Testing Scenarios

To facilitate the evaluation of object detectors under varying weather circumstances, we devised a real test scenario. The videos were captured with a conventional mobile camera, possessing a resolution of 2 megapixels, and keeping to a typical frame rate. The test data was collected under typical outside conditions in order to accurately reflect the realities of various weather conditions during the experiment. Figure 1 shows the sample of foggy weather conditions.

Figure 1: Foggy weather dataset sample

The proposed approach involves capturing video footage of cows crossing roads under various circumstances, encompassing three distinct weather conditions. This methodology aims to provide a sufficient quantity of test materials to facilitate accurate examinations of our pretrained models. There were almost 15 recorded videos captured across three distinct weather situations.

3.2 Evaluation Metrics

To conduct a comparative analysis of the object detectors, we took into account various parameters related to object detection. A Precision-Recall-Curve is generated for each algorithm. The graph illustrates the relationship between precision and recall in relation to ranked confidence scores. Precision is a metric that quantifies the level of precision exhibited by an object detector. Conversely, recall, also known as sensitivity, is a metric that quantifies the number of relevant results that are successfully retrieved[4], [29]. Precision and Recall are defined by Eq. 1 and Eq. 2 respectively:

$$Precision = \frac{true\ positive}{true\ positive + false\ positive} \tag{1}$$

$$Recall = \frac{true\ positive}{true\ positive + false\ negitive} \tag{2}$$

A True Positive (TP) is defined as a detection that is considered correct when its Intersection over Union (IoU) value is greater than a threshold value (t). A False Positive (FP) refers to a detection that is either incorrect or has an Intersection over Union (IoU) value less than a specified threshold (t). The threshold value t for Intersection over Union (IoU) is defined as the minimum value at which the IoU of a bounding box is deemed to be acceptably accurate. A False Negative (FN) refers to a ground truth that remains undetected as a result of a confidence score that is relatively low. In addition, the Average Precision (AP) is computed for each object detector, representing the estimated area under the Precision-Recall Curve[25]. It is defined by Eq. 3:

$$Ap = \sum_{n=0} (r_{n+1} - r_n)\, pinterp(r_{n+1}) \tag{3}$$

The interpolated precision $pinterp(r_{n+1})$ is defined by taking the maximum precision at each recall level r, where the corresponding recall value is greater than rn+1. In another word it is only the area under the Precision-Recall-Curve[25].

3.3 Dataset Preparation

Data preparation is a crucial step in object detection before feeding to the model for processing and detection. In this study a new dataset has been created and utilized for evaluating the proposed method. A set of 15 videos captured in typical outdoor weather conditions was utilized as the dataset for this study. Five of the movies were captured under typical weather circumstances, while the remaining ten movies were filmed in fog and night mode. All videos remained unedited in order to maintain their normality. In order to conduct a comprehensive evaluation of the detectors, all frames have been extracted from the movies, to ensure a fair and unbiased testing procedure. The dimensions of each frame were reduced to a resolution of 480 × 600 pixels. A big number of frames comes when converting the input videos to frames using the frame rate of 24 per second, continuously all will be added on each other to create the resulted video which going to be used to select some useful frames for the evaluation process. Table 1 shows the details of information related to the dataset.

Table 1: Details of dataset for each video.

Video	Mode	Duration in seconds	No. of Frames	No. of Objects in Video
1	Clear Day	32	768	6

2	Clear Day	35	840	5
3	Clear Day	10	240	7
4	Clear Day	20	480	4
5	Clear Day	25	600	2
6	Foggy	30	720	10
7	Foggy	30	720	9
8	Foggy	20	480	4
9	Foggy	15	360	6
10	Foggy	10	240	6
11	Night Mode	30	720	6
12	Night Mode	10	240	5
13	Night Mode	10	240	8
14	Night Mode	15	360	3
15	Night Mode	20	480	4

3.4 Object Detection

To assess the performance of object identification algorithms in varying environmental situations, we have selected two algorithms for evaluation: SSD and YOLOv8. These algorithms will be tested under normal, night, and foggy conditions. Both of these methods demonstrate the ability to accurately recognize objects in real-time. Each individual employs a pre-existing weight file that has been trained on the COCO dataset. The training split of the COCO dataset has a total of 118,000 images or more, which are utilized for training purposes[22],[30],[31]. However, the focus of this study was limited to the cow species. We have selected varying confidence rates for each algorithm, which exhibit differences in their training methodologies and object detecting capabilities. This provides us with a more comprehensive understanding of the behavior of algorithms and the impact of confidence on performance. The MobileNetSSD model was selected for the SSD framework, while the Ultralytics YOLOv8 model was picked for the YOLOv8 framework. Every instance of object detection was performed on every video inside the dataset, resulting in the prediction of a confidence score and a corresponding bounding box using the YOLO algorithm or a large dot using SSD.

3.5 Confidence Level

Within the context of object detection models, the "confidence level" or "confidence score" pertains to a numerical number provided to each identified item, serving as an indicator of the probability that the detection is accurate. The score typically ranges from 0 to 1, with higher values indicating a greater degree of reliability in the detecting process.

In the context of object detection, it is necessary to provide more elaboration on the operational mechanisms involved.

A. Bounding box: In the context of object detection models, it is customary for these models to generate a bounding box that encompasses the identified item inside an image.
B. Class label: The model often includes a class label in addition to the bounding box, which serves to identify the type of item that has been recognized, such as "dog," "car," and so on.
C. Confidence level: The model will generate a confidence score for each bounding box and corresponding class label. This estimate quantifies the level of confidence that the model possesses regarding the presence of an item belonging to the anticipated class within the bounding box[25].

The use of a confidence score threshold can be employed as a means of filtering away detections that are deemed to be less reliable. As an illustration, it may be desirable to exclusively take into account detections that possess a confidence score beyond 0.8 (or 80%). Ranking can be utilized in scenarios where numerous bounding boxes are recognized; confidence ratings can be employed to establish a hierarchy based on their respective levels of dependability. Moreover, for evaluation measures confidence ratings play a crucial role in the computation of performance measures for the model, such as Precision, Recall, and the F1 score. This is particularly significant when assessing metrics like average precision (AP).

In this study the detection threshold values were established at 0.25, 0.50, 0.75, and 0.90. This implies that the outcomes have been categorized into four distinct levels of projected confidence. Hence, the outcomes of this study are influenced by the utilization of multiple levels of confidence, as exemplified by the frequency of reliable recognition in cases of low confidence within the setting of poor vision. Additionally, there were instances of incorrect detections occurring at a low degree of confidence, providing a valuable opportunity to assess and compare the performance of the tested models. On the contrary, an elevated degree of confidence might contribute to a reduction in false detections, therefore enabling the assessment of a model's performance[26].

3.6 Experimental Results Collection

To fulfill the efficiency of both SSD and YOLO, we have conducted many experiments in different confidents levels to calculate the accuracy of each level in different weather conditions. The results out putted as videos from the python prepared code that contains the models of objects detection. That videos latterly converted to sequenced frames selected when the cows crossing the roads (both models tested for the same equal videos and same frames taken to meet a fair experiments). In this stage of collecting results I have to point that many frames were extracted because of redundancy. Next from each selected frame TP, FP, and FN values collected as shows in the Figure 2 bellow.

Figure 2: Selected frame TP, FP, and FN values.

All experiments were done successfully as planned and the results showed the following:

3.6.1 Normal Weather Experiment

Five experiments are conducted in normal weather in different confidential ratios as it appears in Table 2. The experiments accuracy results are shown in Figure 3 to Figure 6 bellow:

Figure 3: Accuracy of 25% confident in normal weather.

Figure 4: Accuracy of 50% confident in normal weather.

Figure 5: Accuracy of 75% confident in normal weather.

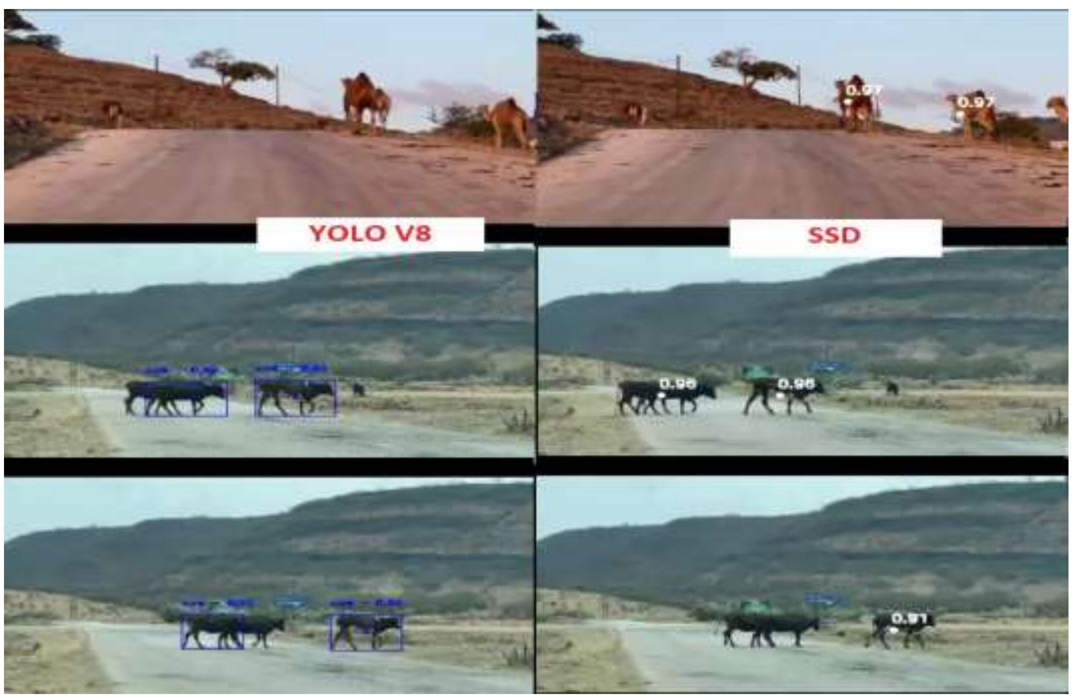

Figure 6: Accuracy of 90% confident in normal weather.

Table 2: Performance in normal weather.

	SSD		YOLO	
Confident level	**Recall**	**F1 score**	**Recall**	**F1 score**
25%	0.71	0.77	0.95	0.85
50%	0.72	0.78	0.94	0.97
75%	0.55	0.66	0.77	0.82
90%	0.42	0.55	0.55	0.71
Average	0.6	0.69	0.81	0.84

3.6.2 Foggy Weather Experiment

Also, the models are experimented in foggy weather with same ratios as it appears in Table 3.3. The experiments accuracy results for foggy weather are shown in Figures 7 to Figure 10 bellow:

Figure 7: Accuracy of 25% confident in foggy weather.

Figure 8: Accuracy of 50% confident in foggy weather.

Figure 9: Accuracy of 75% confident in foggy weather.

Figure 10: Accuracy of 90% confident in fogy weather.

Table 3: Performance in foggy weather.

	SSD		YOLO	
Confident level	**Recall**	**F1 score**	**Recall**	**F1 score**
25%	0.18	0.30	0.66	0.17
50%	0.09	0.17	0.28	0.32
75%	0.06	0.11	0.19	0.44
90%	0.00	0.00	0.10	0.80
Average	0.08	0.15	0.31	0.43

3.6.3 Night Mode Experiment

Third experiment is conducted in night mode using same confident ratios as it appears in Table 4 and the experiments accuracy results are shown in Figures 11 to Figure 14 bellow:

Figure 11: Accuracy of 25% confident in night weather.

Figure 12: Accuracy of 50% confident in night weather.

Figure 13: Accuracy of 75% confident in night weather.

Figure 14: Accuracy of 90% confident in night weather.

Table 4: Performance in night weather.

	SSD		YOLO	
Confident level	**Recall**	**F1 score**	**Recall**	**F1 score**
25%	0.03	0.05	0.94	0.97
50%	0.04	0.08	0.75	0.85
75%	0.04	0.08	0.51	0.68
90%	0.04	0.08	0.06	0.13
Average	0.04	0.08	0.57	0.65

4. Evaluation and Results Discussion

This section presents the outcomes of the object detection algorithms used to our recorded dataset. Initially, an examination will be conducted to assess the impact of fluctuating weather conditions on the outcomes of detection and the accuracy of projected bounding boxes. Next, we examine the metrics of precision and recall, construct a Precision-Recall-Curve, and compute the Average Precision (AP) for each approach under three distinct weather situations. It is important to acknowledge that inference time was not taken into consideration throughout our study.

To assess the detection capabilities, we conducted an evaluation by applying each object detector to every frame within our dataset across four confidence stages: 25%, 50%, 75%, and 90%. The videos are saved with enhancements in the form of labels applied to the recognized objects across many frames. The conclusive outcomes will be derived from the images obtained by capturing videos. The recorded assessment results of all algorithms were obtained by analyzing the captured frames in various environmental situations, including normal, foggy, and night mode as shown in Table 5.

Table 5: Accuracy performance in mean for all weathers

Model	Clear Day AP	Foggy Weather AP	Night mode AP	mAp
YOLO V8	96%	64%	94%	84.67%
SSD	59%	18%	5%	27.33%

The performance of the pretrained MobileNet SSD model was satisfactory under clear weather conditions, with an average precision of approximately 60%. The real-time object detection demonstrated acceptable levels of efficiency. In contrast, the YOLO V8 model exhibited significantly superior results, achieving a performance level of 96%, hence outperforming all other experiments in our studies.

The presence of foggy weather negatively impacts both models. Regrettably, the MobleNet SSD exhibited limited efficacy in detecting the presence of cows during their crossing of the road. The average precision is limited to a mere 18%. Simultaneously, the trials demonstrate that the YOLO V8 pretrained model has enhanced visual perception, with an average precision of 64%. This indicates a notable proficiency in recognizing objects even under adverse weather conditions. The exceptional demonstration illustrates the sophisticated level of improvements implemented in YOLO V8.

The implementation of night mode has resulted in a widening disparity between the two models being tested. The YOLO V8 model demonstrates a negligible impact when its average precision closely approximates that of the clear weather model, reaching 94%. However, the MobileNet SSD model's vision is significantly diminished, as seen by its average precision of only 5%. The efficacy of this vision is modest, although it remains functional when considering its nature as a real-time object detection model. On the contrary, it is worth noting the remarkable progress achieved in the YOLO V8 model.

Both models demonstrated overall effectiveness. The YOLO V8 model achieved a mean average precision of 84.67% over all three weather situations. The SSD model's mean average precision yielded a value of 27.33% over three distinct weather tests. Figure 4.1 shows the result analysis for precession , recall and F1 for normal weather.

4.1 Analysis of the Normal Weather Charts

The true positive (TP) refers to the number of correct detections made by both models, which typically tends to increase in areas with lower confidence. The identification of errors is referred to as false positives (FP), which ideally should only occur in areas of low confidence. However, a small indication of these issues may be observed in the 90% confidence interval of the SSD model. This suggests the presence of a potential problem inside the model that should be addressed by those seeking to enhance its performance. The occurrence of false negatives (FN), which refers to undetected cows, has been found to rise in high confidence areas in both models, as expected.

The recall and F1 score exhibited a consistent upward trend in the low confidence regions, while experiencing a decrease in the high confidence regions, as depicted in the recall, precision, and F1 score charts for both models. The level of precision observed in both tested models does not deviate significantly from the expected levels. Due to the high mean Average Precision (mAP) exhibited by both models under clear weather conditions.

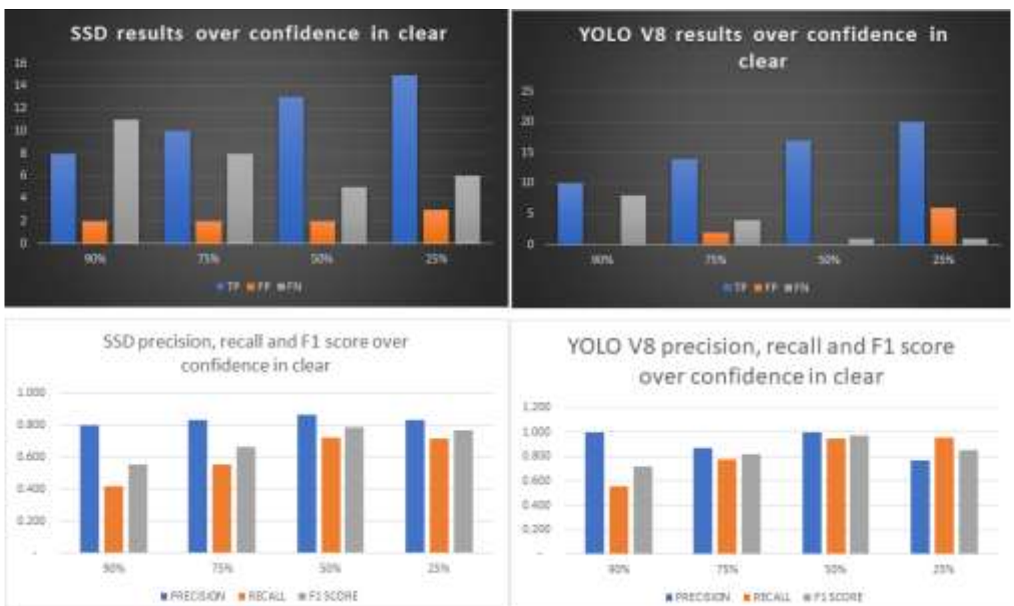

Figure 15: Precession, Recall evaluation in normal weather.

4.2 Analysis of the Foggy Weather Charts

TP count generally tends to rise in regions with lower confidence but appears to be quite low on the SSD side. The act of detecting mistakes is commonly known as false positives (FP), and it is not completely documented in conditions of reduced visibility. The observed phenomenon can be attributed to the presence of a dense distribution of fog, which imparts a similar color to adjacent pixels within the picture[24]. The significant false negative rate observed across all confidence levels in the SSD model indicates a poor mean average precision (mAP). In the recall, precision, and F1 score charts, both models exhibit a typical increase in recall and F1 score values in regions of low confidence, while these values decrease in regions of high confidence. The precision of the confidence levels in both tested models is maximized due to the absence of false negatives.

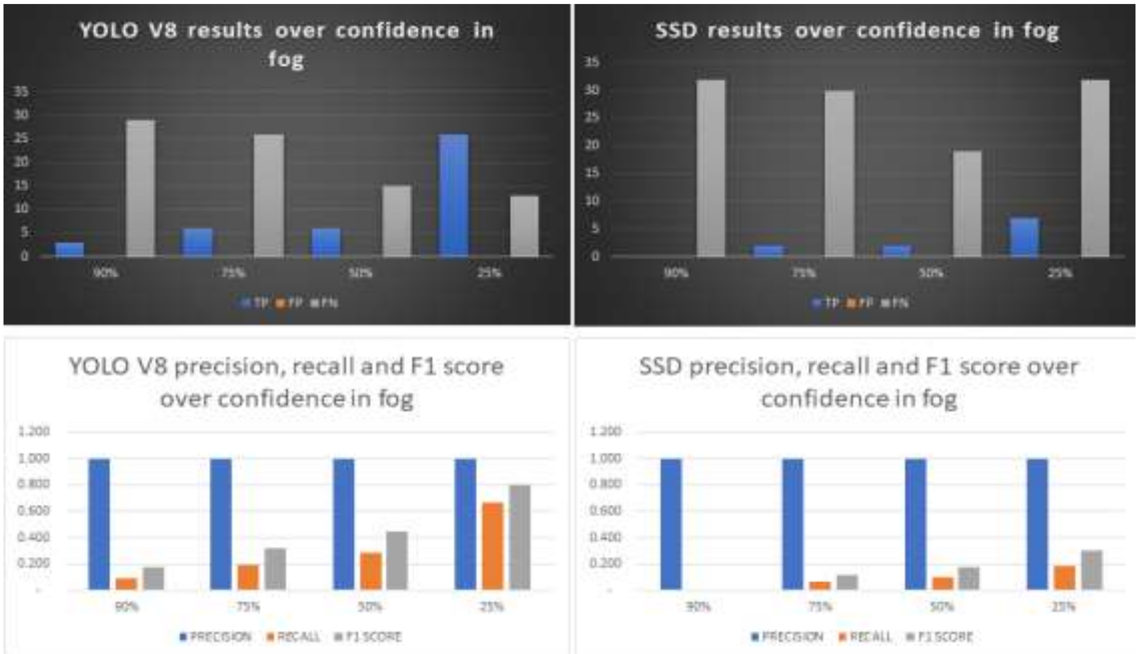

Figure 16: Precession, Recall evaluation in foggy weather.

4.3 Analysis of the Night Mode Charts

In the YOLO V8 chart, there is a general trend of TP (true positive) increasing in regions with lower confidence levels and decreasing in places with higher confidence levels. Conversely, the SSD side of the chart exhibits consistently low TP values throughout all degrees of confidence. The occurrence of false positives (FP) in night mode was found to be extremely infrequent in both models, in contrast to foggy conditions when it was absent. The high false negative rate seen across all confidence levels in the (SSD) model is indicative of a low mean average precision (mAP). The data reveal a significant disparity between the two models during nighttime operation.

The recall and F1 score in the YOLO V8 model exhibit a typical pattern of growth in low confidence regions and decrease in high confidence regions, as observed in the recall, precision, and F1 score charts. Nevertheless, the SSD model exhibits consistently low levels of confidence across all recorded data. Although high precision scores in SSD indicate accuracy, it is important to note that low recall and F1 scores can significantly impact the overall performance.

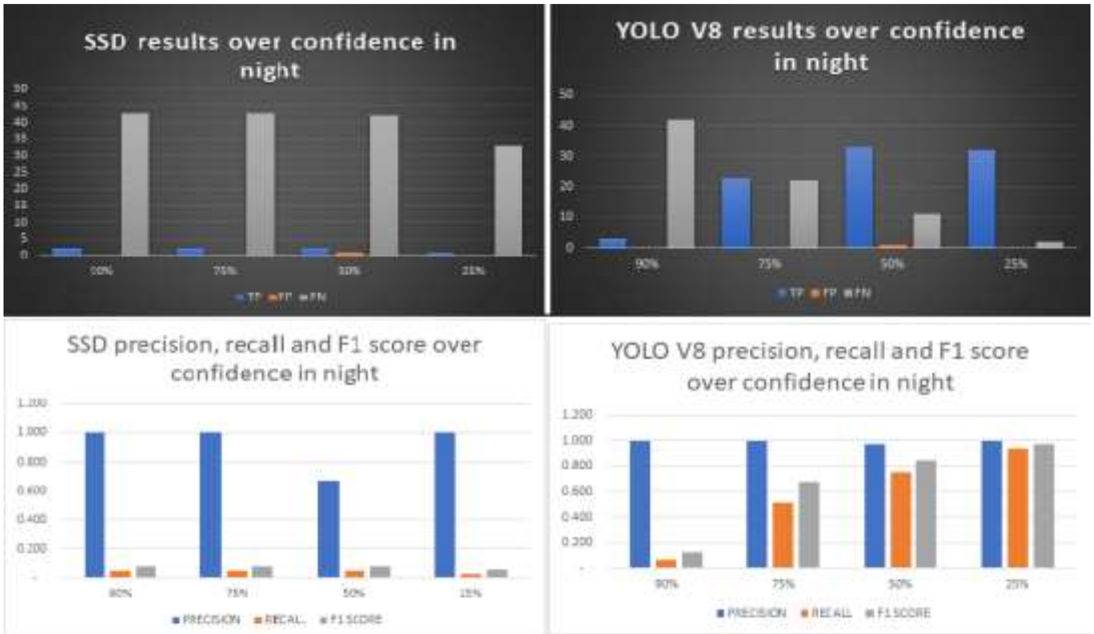

Figure 17: Precession, Recall evaluation in night mode.

5. Conclusion And Future Work

In conclusion, Object detection is a vital discipline that enables robots to employ artificial intelligence to accurately identify and classify a diverse array of objects. This study investigated two distinct algorithms, namely YOLOv8 and SSD, both of which are classified as one-step algorithms. Various algorithms were employed to identify bovine animals under varying environmental situations, including daytime, nighttime, and foggy weather. The YOLOv8 model demonstrated the capability to effectively operate and detect objects across all specified conditions, without any instances of failure or exception. The efficacy of the second method, known as SSD, is limited during nighttime or in environments characterized by fog. In terms of future endeavors, potential advancements may be feasible with regards to the identification of (SSD) under adverse weather circumstances and during nocturnal periods. To boost vision capabilities and improve detection accuracy during adverse weather conditions, it is proposed to develop a novel model. The proposed future prospect model aims to enhance visual clarity by mitigating impediments such as fog. Additionally, it has the potential to enhance luminosity, rendering it appropriate for nocturnal applications. Enhancing the model's performance can be achieved by eliminating obstacles, hence leading to greater detection capabilities in adverse weather conditions and during nighttime. The implementation of a data augmentation technique aimed at generating simulated fog conditions inside the dataset has the potential to further enhance the accuracy and effectiveness of object detection algorithms. Increasing the number of instances depicting adverse weather conditions in the algorithmic training dataset would enhance the model's ability to identify impediments and improve its object detection capabilities in such circumstances. Therefore, it is strongly advised to develop a fresh model utilizing an extensive dataset from the Dhofar region by employing YOLO V8.

6. Conflict of Interest

We have no conflicts of interest to disclose.

All authors declare that they have no conflicts of interest.

7. Data Availability

The data supporting the study's conclusions may be found in the paper's supplementary materials. Additionally, the corresponding author will supply the information needed to substantiate the study's findings upon reasonable request.

REFERENCES

[1] NATIONAL CENTRE FOR STATISTICS & INFORMATIONS, “Oman Satatistics for Security and Safety,” 2021.

[2] Royal Omani Police, “Accedents STATISTICS,” 2022.

[3] A. M. Abu Abdo and A. A. Al-Ojaili, “Assessment of awareness of livestock-vehicle traffic accidents in Dhofar Region, Oman,” *Int. J. Appl. Eng. Res.*, vol. 10, no. 18, pp. 38955–38959, 2015.

[4] A. M. A. ghan. ABDULGHANİ and G. G. MENEKŞE DALVEREN, “Moving Object Detection in Video with Algorithms YOLO and Faster R-CNN in Different Conditions,” *Eur. J. Sci. Technol.*, no. 33, pp. 40–54, 2022, doi: 10.31590/ejosat.1013049.

[5] X. Tian, B. Li, X. Cheng, and X. Shi, “Target detection and cow standing behavior recognition based on YOLOv5 algorithm,” pp. 206–210, 2022, doi: 10.1109/ispds56360.2022.9874008.

[6] W. S. Yuwono, D. W. Sudiharto, and C. W. Wijiutomo, “Design and Implementation of Human Detection Feature on Surveillance Embedded IP Camera,” *3rd Int. Conf. Sustain. Inf. Eng. Technol. SIET 2018 - Proc.*, pp. 42–47, 2018, doi: 10.1109/SIET.2018.8693180.

[7] Y. Q. Ong, T. Connie, M. Kah, and O. Goh, “A Cow Crossing Detection Alert System,” vol. 13, no. August, pp. 1202–1212, 2022, doi: 10.14716/ijtech.v13i6.5874.

[8] W. Yimyam, K. Kocento, and M. Ketcham, “Video Surveillance System Using IP Camera for Target Person Detection,” *Isc. 2018 - 18th Int. Symp. Commun. Inf. Technol.*, no. Iscit, pp. 285–290, 2018, doi: 10.1109/ISCIT.2018.8587927.

[9] S. Santhanam, S. B. Sudhir, S. S. Panigrahi, S. K. Kashyap, and B. K. Duriseti, “Animal Detection for Road safety using Deep Learning,” *2021 Int. Conf. Comput. Intell. Comput. Appl. ICCICA 2021*, 2021, doi: 10.1109/ICCICA52458.2021.9697287.

[10] S. A. Atone, A. S. Bhalchandra, and P. H. Bhagat, “Moving Object Detection with an IP camera,” *Proc. 2nd Int. Conf. Intell. Comput. Control Syst. ICICCS 2018*, no. Iciccs, pp. 1081–1084, 2019, doi: 10.1109/ICCONS.2018.8662963.

[11] X. Huang, X. Li, and Z. Hu, “Cow tail detection method for body condition score using Faster R-CNN,” *2019 IEEE Int. Conf. Unmanned Syst. Artif. Intell. ICUSAI 2019*, pp. 347–351, 2019, doi: 10.1109/ICUSAI47366.2019.9124743.

[12] R. Shanthakumari, C. Nalini, S. Vinothkumar, B. Govindaraj, S. Dharani, and S. Chindhana, “Image Detection and Recognition of different species of animals using Deep Learning,” *2022 Int. Mob. Embed. Technol. Conf. MECON 2022*, pp. 236–241, 2022, doi: 10.1109/MECON53876.2022.9752203.

[13] M. Yan and J. Sun, “A Dim-small Target Real-time Detection Method Based on Enhanced YOLO,” *2022 IEEE Int. Conf. Electr. Eng. Big Data Algorithms, EEBDA 2022*, pp. 567–571, 2022, doi: 10.1109/EEBDA53927.2022.9745012.

[14] R. Zhang, Y. Yang, W. Wang, L. Zeng, J. Chen, and S. McGrath, “An algorithm for obstacle detection based on YOLO and light filed camera,” *Proc. Int. Conf. Sens. Technol. ICST*, vol. 2018-Decem, pp. 223–226, 2019, doi: 10.1109/ICSensT.2018.8603600.

[15] R. Asyrofi and Y. A. Winata, “The improvement impact performance of face detection using yolo algorithm,” *Int. Conf. Electr. Eng. Comput. Sci. Informatics*, vol. 2020-Octob, no. October, pp. 177–180, 2020, doi: 10.23919/EECSI50503.2020.9251905.

[16] A. Sarda, S. Dixit, and A. Bhan, “Object Detection for Autonomous Driving using YOLO algorithm.,” *Proc. 2021 2nd Int. Conf. Intell. Eng. Manag. ICIEM 2021*, no. Icicv, pp. 447–451, 2021, doi:

10.1109/ICIEM51511.2021.9445365.

[17] M. B. Ullah, "CPU Based YOLO: A Real Time Object Detection Algorithm," *2020 IEEE Reg. 10 Symp. TENSYMP 2020*, no. June, pp. 552–555, 2020, doi: 10.1109/TENSYMP50017.2020.9230778.

[18] M. Hussain, "YOLO-v1 to YOLO-v8, the Rise of YOLO and Its Complementary Nature toward Digital Manufacturing and Industrial Defect Detection," *Machines*, vol. 11, no. 7, p. 677, 2023, doi: 10.3390/machines11070677.

[19] M. Mahendru and S. K. Dubey, "Real time object detection with audio feedback using Yolo vs. Yolo_V3," *Proc. Conflu. 2021 11th Int. Conf. Cloud Comput. Data Sci. Eng.*, pp. 734–740, 2021, doi: 10.1109/Confluence51648.2021.9377064.

[20] H. He, "Yolo Target Detection Algorithm in Road Scene Based on Computer Vision," *2022 IEEE Asia-Pacific Conf. Image Process. Electron. Comput. IPEC 2022*, pp. 1111–1114, 2022, doi: 10.1109/IPEC54454.2022.9777571.

[21] A. Corovic, V. Ilic, S. Duric, M. Marijan, and B. Pavkovic, "The Real-Time Detection of Traffic Participants Using YOLO Algorithm," *2018 26th Telecommun. Forum, TELFOR 2018 - Proc.*, pp. 9–12, 2018, doi: 10.1109/TELFOR.2018.8611986.

[22] ultralytics yolov8, "YOLOv8 Docs," 2021.

[23] W. Liu *et al.*, "SSD: Single shot multibox detector," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 9905 LNCS, pp. 21–37, 2016, doi: 10.1007/978-3-319-46448-0_2.

[24] Á. Morera, Á. Sánchez, A. B. Moreno, Á. D. Sappa, and J. F. Vélez, "Ssd vs. Yolo for detection of outdoor urban advertising panels under multiple variabilities," *Sensors (Switzerland)*, vol. 20, no. 16, pp. 1–23, 2020, doi: 10.3390/s20164587.

[25] T. Rothmeier and W. Huber, *Performance Evaluation of Object Detection Algorithms Under Adverse Weather Conditions*, vol. 364 LNICST, no. 13. Springer International Publishing, 2021. doi: 10.1007/978-3-030-71454-3_13.

[26] Z. Li and J. Wang, "An improved algorithm for deep learning YOLO network based on Xilinx ZYNQ FPGA," *Proc. - 2020 Int. Conf. Cult. Sci. Technol. ICCST 2020*, pp. 447–451, 2020, doi: 10.1109/ICCST50977.2020.00092.

[27] Keras API, "MobileNet, MobileNetV2, and MobileNetV3," 2022.

[28] V. R. Kumari and P. S. Sanjay, "Smart Surveillance Robot using Object Detection," *Proc. 2020 IEEE Int. Conf. Commun. Signal Process. ICCSP 2020*, pp. 962–965, 2020, doi: 10.1109/ICCSP48568.2020.9182125.

[29] H. Yu, Y. Li, and D. Zhang, "An Improved YOLO v3 Small-Scale Ship Target Detection Algorithm," *Proc. - 2021 6th Int. Conf. Smart Grid Electr. Autom. ICSGEA 2021*, pp. 560–563, 2021, doi: 10.1109/ICSGEA53208.2021.00132.

[30] A. Howard *et al.*, "Searching for mobileNetV3," *Proc. IEEE Int. Conf. Comput. Vis.*, vol. 2019-Octob, pp. 1314–1324, 2019, doi: 10.1109/ICCV.2019.00140.

[31] Mishra, P., Salman, D., Kumari, B., Al Khatib, A. M. G., & Alshaib, B. M. (2025). Multi-model forecasting framework for agricultural nutrient dynamics in India: a comparative analysis of ML and hybrid approaches for NPK consumption. Cogent Food & Agriculture, 11(1), 2576632. doi.org/10.1080/23311932.2025.2576632

اكتشاف عبور الأبقار للطريق باستخدام YOLOv8 وSSD

محمد العوائد [1*] ، ناصر المصلحي[2]
[1] قسم هندسة الحاسوب، جامعة قبرص الدولية، نيقوسيا، شمال قبرص، مرسين 99258 ، تركيا
[2] كلية دراسات الحاسوب ، الجامعة العربية المفتوحة ، سلطنة عمان

الملخص:
شهدت سلطنة عُمان زيادة ملحوظة في حوادث السيارات الناتجة عن الأبقار السائبة على الطرقات، مما أدى إلى ارتفاع كبير في أعداد الوفيات والإصابات. تهدف هذه الدراسة إلى مقارنة دقة خوارزميتي الكشف عن الأجسام YOLOv8 و SSDفي اكتشاف الأبقار أثناء عبورها الطرق تحت ظروف مناخية مختلفة في منطقة ظفار، وذلك لتحسين السلامة المرورية وتقديم رؤى مفيدة للجهات المسؤولة عن مراقبة الطرق. تعتمد المنهجية على إنشاء مجموعة بيانات مكوّنة من 15 مقطع فيديو توثّق عبور الأبقار في ظروف مناخية متنوعة. كما تتضمن الدراسة تقييم دقة الكشف عند مستويات مختلفة من الثقة (25%، 50%، 75%، 90%)، وجمع النتائج من حيث الإيجابيات الحقيقية(TP) ، والإيجابيات الكاذبة(FP) ، والسلبيات الكاذبة.(FN) . تكشف النتائج التجريبية أن خوارزمية YOLOv8 تتفوق باستمرار على SSD في جميع الظروف الجوية. ففي الأجواء الصافية خلال النهار، حقق YOLOv8 دقة كشف بلغت 96% مقارنة بـ SSDالذي حقق 59%. وفي الظروف الضبابية، حافظ YOLOv8 على دقة قدرها 64% مقابل 18% لـ .SSDأما في ظروف الليل، فقد برز YOLOv8 بدقة بلغت 94%، في حين سجّل SSD نسبة 5% فقط. وبشكل عام، حقق YOLOv8 متوسط دقة عام يبلغ 84.67% عبر جميع الحالات، بينما بلغ متوسط دقة.27.33% SSD . وتؤكد هذه النتائج أهمية اختيار نموذج الكشف عن الأجسام المناسب تبعاً للظروف الجوية المختلفة من أجل تحسين السلامة على الطرق.

الكلمات المفتاحية: تصنيف الأجسام، كشف الأجسام، تتبع الأجسام، SSD، YOLO.