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Comparison of Image segmentation, HOG and CNN Techniques for the Animal Detection using Thermography Images in Automobile Applications

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***Abstract*— Animal Vehicle Collision is an inviolability concern that comes with the cost of both humankind and animals. It has popularly resulted in millions of deer-vehicle collisions claims and fatalities. The only way to prevent the above-saddened statics is to drive wildlife safely away from roadways due to morbidity and injuries. This paper undrapes the optimal comparative study between edge-based image segmentation and CNN-HOG for self-acting animal detection. As the fatal crashes peaks during nighttime, night vision image detection is focused on this paper with the mounted camera in the vehicle. Edge-based image segmentation is applied to the intelligent animal detection system to demonstrate the prowess of animal detection. The intelligent system processes thermographic images and feature extractions used for the object existence prediction. Deer is the overly populated animal and most commonly spotted animal used as the subject of detection in this research. The animal detection is done using the Histogram of Oriented Gradient (HOG) transform, whereas optimization is demonstrated using image segmentation. Image segmentation helps in precise animal detection by extending the continuity of the images, which is crucial for image processing during detection. The results vividly conclude the contribution of image segmentation accuracy to the existing HOG-based intelligent system with 91% accuracy using the wide roadsides of San Antonio, TX, in the USA.**

Keywords*— *deer-vehicle crashes, thermal images, edge detection, image segmentation, histogram of oriented gradients (HOG), 1d convolutional neural network.

I. Introduction

The Deer-Vehicle collisions are not only expensive but also very detrimental to the human-animal ecosystem. The unpredictable and erratic nature of wild animals always results in severe injuries and fatal crashes. Wildlife Collision Prevention program always warns drivers to be cautious about driving during nocturnal and animal mating season. With the rapid increase of computer vision and profound learning advancement, vehicles should automatically detect and prevent such fatal collisions. Adaptive cruise control and Autonomous braking are the automobile safety advancements in imminent collisions. However, they have not mitigated the animal-vehicle collisions where the animal behavior is unpredictable and the time to respond is compassionate. In addition to automobile safety, driver assistance technologies have prevented imminent collisions. The existing technologies and tools still have areas of improvement in animal existence and its behavioral detection. Wildlife signage and wildlife crossing bridges have reduced the collision rate but could not eradicate it, so we need an intelligent solution to this underlying problem.

Deer is the primary reason behind overall US wildlife crashes, estimated to be 35,000 annually [1]. According to the Havahart survey, 60% of the collision always resulted in animal death. According to Statefarm, from July 1, 2019, to June 30, 2020, deer claims are estimated to be 1.5 million industry-wide. Deer appears 25times more than other animals in the animal collision claims, and most of them go unreported. The proposed intelligent system does a thorough study of image detection and image segmentation as comparative study metrics.

In this paper, to avoid real-time accidents across the roadsides, a new intelligent system is proposed and designed. The goal is to increase the accuracy of the HOG transformation with the CNN intelligent model [2][3]. Combining image segmentation with HOG transformation will enhance the detection of the object from the given image [4]. For instance, the author in [5] describes the K-means clustering-based image segmentation. This type of segmentation is used to segment the image into various regions based on similar pixel values compared with the neighbor pixel relationship. After the basic technique, the grouping of similar pixels, the contours are measured by the edge detection and then convolve, subtract and boost the frequency components of the image. The entirely convoluted layers are used to identify the segmented images, and also, by upsampling and downsampling, they achieved the image segmentation.

Furthermore, semantic segmentation is also achieved by this CNN technique [6]. Local Binary Pattern (LBP) is used for the texture spectrum measure, and it is used in the areas like text identification and face recognition. Combining LBP with the HOG transform will increase the accuracy in detection. Then the identified objects are processed with the machine learning algorithm to improve the efficiency of the detected images [7].

The Region of Interest (ROI) is the first step in image segmentation for the thermography images. The selection of ROI is in different shapes like circular, rectangle ellipse, or squares. [8]. There are different types of image segmentation. The main split-up of image segmentation is based on discontinuity detection and similarity detection [9]. The other methods are threshold-based, region-based, watershed-based, edge-based, and clustering-based image segmentation techniques. In this paper, edge-based image segmentation is taken into consideration to enhance the accuracy of detection.

During this process, the main parameter to be considered is the time length of the whole testing procedure. The CNN-based image segmentation is excellent for producing remarkable results; by replacing the fully connected layer as fully convoluted layers, image segmentation occurs in the given image dataset [10]. The following method is the thresholding-based image segmentation that will enhance the detection accuracy. The global thresholding method converts the images into the binary form [11][16]. The characteristics of the thermal and night vision images are different in contrast, texture radiation, and reflection. During the nighttime, it very hard to identify the object in the pavements. This is happening because of the factors mentioned above. The animals will have high blood temperature compared with their environment [12]. The difference between the background and the image will be determined based on this feature.

By all this evidence, in this paper, image segmentation-based HOG transform, thermal images, and 1D Convolutional Neural Network are considered for the intelligent system design. Dataset of images is collected from the San Antonio, TX, surrounding area during nighttime. Because of the close value temperatures, the originality of the thermal idea is differing.

The prominence of this research is in training the artificial intelligence system and enhancing the proficiency of the image detection diagnosis. Our proposed intelligent system builds upon image segmentation with HOG transform and a synergistic CNN model to enhance detection accuracy [13]. The primary application of this research is for automobiles, and this contributes to innovative car development.

The structure of this article is as follows: Section II describes the basic acquaintance about the image segmentation and its types, and HOG transform and explains the literature survey of different systems, which paves direction for this research. Section III describes the diagrammatic representation of the methodology of the intelligent system design. Section IV examines the comparison results and verdicts of the proposed intelligent system design, whereas the bar charts and the tabulated values show the experimental outputs. Section V discusses and concludes the best detection method from the proposed systems.

II. Image Segmentation and Histogram of Oriented Gradients (HOG)

This section elucidates in detail the basic concepts of Image segmentation and its types, HOG transform, and its types.

A. Image Segmentation

Image segmentation is the challenging computer algorithm to perform digital image processing on images. This technique is used to partition the given digital image based on their wanted similar features and properties. It is one of the techniques where unwanted information is simplified by representing meaningful information. The goal of image segmentation is to divide the image into several segments based on their similar attributes. The other purpose of image segmentation is to change the image representation to make the analysis faster than ever. The properties of the images are shape, edge, size, intensity, texture, object, and orientation. The segmentation technique will work based on any one of these properties. Image segmentation is used in object detection and recognition, video surveillance, and automatic traffic control systems.

B. Types of Image Segmentation

The image segmentation is divided into different types based on the properties of the image, namely thresholding segmentation, region-based segmentation, and edge-based segmentation. All these types are based on the continuity and discontinuity of the pixels in the image. The edge detection segmentation is based on intensity discontinuity, and it is used to find the object's boundaries. The region-based and thresholding segmentation techniques are based on the similarity of the object's appearance [14]. In this research, edge-based segmentation is used to determine the discontinuity of the intensity value.

C. Image Segmentation - Overview

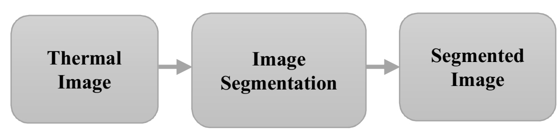

Fig. 1. General Block Diagram for Image Segmentation

Fig. 1. shows the fundamental steps involved in image segmentation. The original thermal image is given into the edge-based segmentation; the vertical-based edges are determined using the Sobel operators. In the same way, the horizontal edges of the objects are determined by the operators. The Laplacian kernel operator calculates both the horizontal and vertical edges. Then the segmented image is fed into another feature detection pre-processing image technique called HOG transformation.

D. Histogram of Oriented Gradients Transformation

HOG is a pre-processing tool used for object detection in computer vision. This method calculates the magnitude gradient and orientation of the given image. The similar transform methods for these HOG transforms are edge detection and scale-invariant feature transform (SIFT). HOG is used in different applications like pedestrian detection, human detection, animal detection, and vehicle detection. This feature descriptor plays a vital role in detecting the object based on the characteristics like dimension and color.

E. HOG - Overview

The HOG transformation uses HOG descriptors to find the feature vectors of the image. The general or standard procedure of the HOG is shown for both the thermal and segmented image inputs in Fig.2.

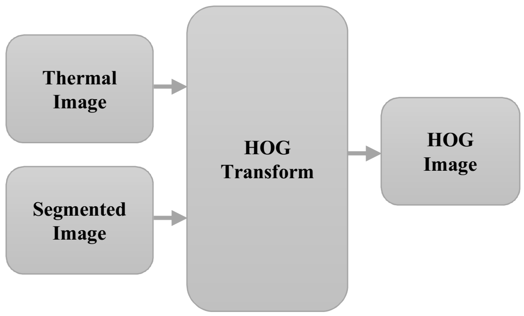

Fig. 2. General Block Diagram for HOG Transformation

Fig. 2. provides the steps involved in the HOG transformation. Before this process, the image must be filtered (resizing, cropping) to make the print ready for the whole process. The image segmentation technique is used to segment the image based on the intensity discontinuity of the picture. These filtering techniques in embodiments increase the quality of the dataset. The HOG algorithm includes gradient computation, defined as the partition of the image into cells, and calculates the direction measure inside the cell. The orientation binning is limited as the discretization of every cell depends on the orientation of the arrow direction. Descriptor block formation is for the grouping of cells into blocks. Finally, block normalization is used to normalize the block histogram, which is called the descriptor.

The above details pertained to the image segmentation, and the HOG algorithm is applied to the current work is detailed in the following section.

III. METHODOLOGY

The proposed methodology and its algorithmic descriptions are discussed in this section. The three significant portions of the proposed system, namely, the image segmentation, HOG, and CNN algorithms, and its comparison, are detailed. The research proposed methodology comprehends the original thermal image, image segmentation, HOG transformation, feature extraction, segmented image, HOG image, convolutional neural network, and confusion matrix from a commoner perception. Comparing HOG-CNN and Image segmentation on top of HOG-CNN will depict the best detection method for the thermal images during the nocturnal period.

A. Block Diagram

This block diagram division describes the image segmentation, histogram of oriented gradients, and convolutional neural networks. Also, this section explains in detail the methodology of the proposed system, sequential steps, and the synergistic steps of the image segmentation, HOG, and CNN techniques.

B. Edge Based Image Segmentation Algorithm

The previous section shows the general description of edge-based image segmentation, whereas the detailed depiction of the segmentation algorithm is given below,

- Step 1: Convert the RGB image into a grayscale image.
- Step 2: Differencing and smoothing by Sobel filters.
- Step 3: Laplacian kernel to segment the given image.
- Step 4: Convolve the Laplacian kernel image.
- Step 5: Generate the segmented image.

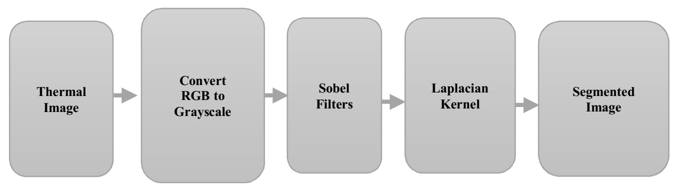

Fig. 3. Detailed Block Diagram of Edge Based Image Segmentation

Fig. 3. detail the steps involved in the edge-based image segmentation. Binary thermal images cannot be processed directly. For further processing, the image has to be operated with the Sobel filters for differencing and smoothing the grayscale binary image. Sobel filters generate the vertical edges and horizontal edges of the image, as shown in Fig. 4. The laplacian kernel operator calculates both the horizontal and vertical edges. Next, the original and Laplacian kernel-based image is convolved to generate the segmented image.

1	2	1
0	0	0
-1	-2	-1

-1	0	1
-2	0	2
-1	0	1

1	1	1
1	-10	1
1	1	1

Fig. 4. Sobel filters and Laplacian Kernel

C. HOG Algorithm Description

An overview of the HOG transform description is given in the previous section, while the complete explanation of the HOG algorithm is detailed below,

- Step 1: Local Normalization.

- Step 2: Gradient calculation.
- Step 3: In each 8x8 cell, HOG is calculated.
- Step 4: Global Block Normalization (16x16).
- Step 5: Generate and flatten the HOG feature vector.

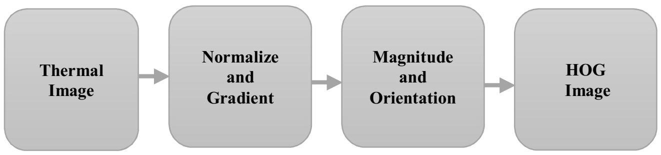

Fig. 5. Detailed Block Diagram for HOG Transformation

The Fig. 5. details the steps involved in the HOG transformation process. For comparison purpose, both the segmented image of dimension 128 x 128 on top of the HOG and the input original thermal image of dimension 480x640 from the directory is called and fed into the HOG transformation. Before the comparison process starts, the authentic thermal images will undergo pre-processing like resizing and cropping to remove the unnecessary information and camera brand logo. Secondly, the whole image is normalized by intensity 0 to 255, which gives the normalized image. The output from step 1 is fed into the next step for gradient computation; based on the pixel intensity values, the gradients g_x and g_y of the image are calculated.

The magnitude gradient and orientation bin are calculated based on the parameters of the HOG, such as blocks and pixel per cell, cells per block, and the number of blocks per image.

$$g = \sqrt{g_x^2 + g_y^2} \qquad (1)$$

$$\theta = \arctan(\frac{g_x}{g_y}) \qquad (2)$$

The magnitude and orientation of the image are calculated by equations (1) and (2). From equation (1), 'g' is the magnitude of the Sobel operator g_x and $g_{y.}$ $_T$he magnitude values of both the vertical and horizontal operator, by squaring and taking square root these two, the magnitude is determined. From equation (2), $'\theta'$ denotes the orientation bin concerning operators g_x and $g_{y.}$ The process is always depending on the continuity of the pixels for identifying the edges of the object. 'L1 norm' is used for block normalization, removing the redundant details from the image, which helps generate and flatten the HOG feature values in vector form. The rescaling intensity extracts the features with a range of 0 to 255. These images are utilized as an input for the CNN optimal results.

D. Proposed System Setup

This chapter describes in detail the methodology of the proposed intelligent system. Here python v3.6 is used as the platform for the simulation [17]. The input thermal image sample with and without an animal is shown in Fig. 6.

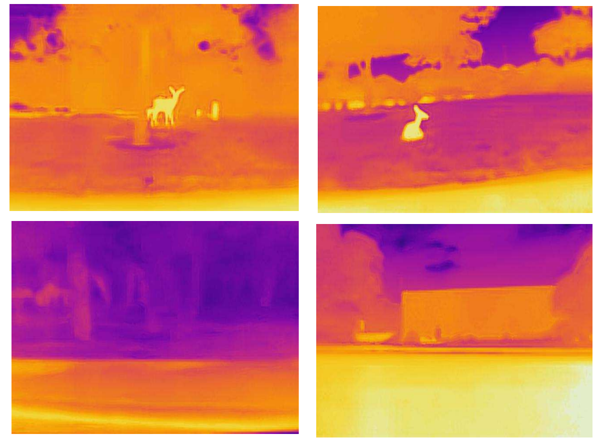

Fig. 6. Sample input with and without thermal deer image

The FLIR ONE Pro brand thermal camera captures the thermal images; this camera will work on the higher and longer wavelength synergism. This thermal camera will have the capacity to capture both coolers (appears in purple-blue or green color) and warmer (appears as red, yellow, or orange) objects with a size of 640x480. The image in Fig. 6. is captured at nighttime, whereas the body and blood temperature of the deer is more visible for thermal cameras. Due to the higher and longer wavelength radiation emission, object detection is much easier for the system or human driver. The thermal image is converted into the HOG image by the feature detection method. In the HOG image, the presence of deer is detected by the continuity in the orientation direction.

Fig. 7. Edge-based image segmentation images

Fig. 7. shows the segmented image from the given thermal input image, which is also used as an input for the only HOG-CNN for comparison. The unwanted information like the image's background captured and wild animals include curb, tree, sky, road, and branches. Due to the lower temperature range, background objects will lose their prominence in image detection. Significantly, the segmented image will optimize the high contrast portions in the thermal image. Therefore, the edges and continuity of the objects will make the input image much clear for the detection using HOG transform.

The following steps are the standard methodology used in the proposed intelligent system, and it is split into two stages as follows,

- Step 1: Thermal Image acquisition
- Step 2: Load the image files as a folder directory
- Step 3: Input images are pre-processed.
- Step 4: Edge-based segmentation process – Generates the Segmented Image.
- Step 5: Fed the input thermal images from Step 3 and segmented images from step 4 to HOG for comparison.
- Step 6: HOG transformation - features are taken into consideration and generates a HOG image.
- Step 7: Flatten and append all the features into 1D vector values.
- Step 8: Split the data for training and testing as 80% and 20% or 70%and 30%.
- Step 9: Use 1D-CNN for training and testing with different convolution layers, activation functions, filter, kernel, dense, and max pooling.
- Step 10: From the generated confusion matrix, calculate the detection accuracy and losses.

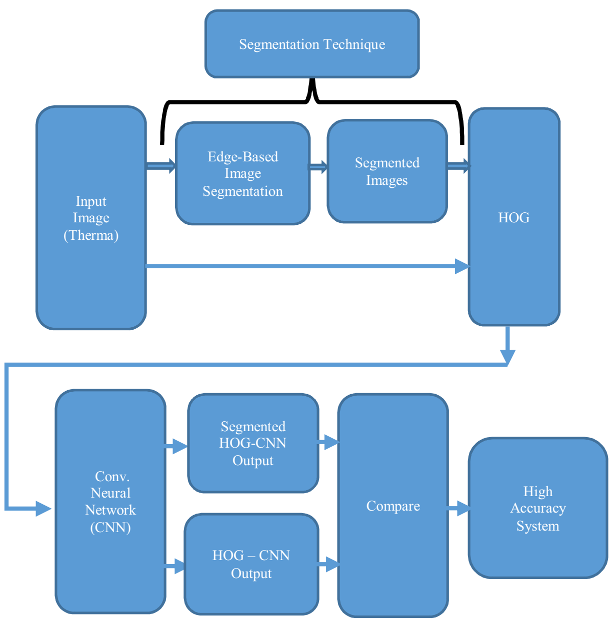

Fig. 8. Block Diagram of the Proposed Intelligent System

Fig. 8. states the proposed intelligent system whole process. The pictorial representation shows the whole research idea in detail. The generated dataset has original thermal images captured by the FLIR ONE Pro thermal camera with a dimension of 640x480. The characteristics of thermal or infrared features make all the images resemble more similar in color and resolution. The similarity will increase the complexity of the process. Pre-processing is required to complete the dataset better for the remaining process. Pre-processing like cropping and resizing are needed to make the process much faster and better. Next, the ready input images are feed into the edge-based segmentation. The output from the segmentation technique and the original thermal images are fed separately to the HOG transform for comparison. The two different inputs with the same number of images will give HOG a transformed image. Then the two outputs of the HOG transform will be saved in two separate folders in the list of arrays. Then the HOG images and the segmented HOG images are testified by the machine learning algorithm.

Convolutional Neural Network is used in this paper for training, validation, and testing for object detection. The HOG output image, such as segmented HOG images and HOG transform images, are fed into the 1D – CNN. The feature detection of the CNN generates a list of arrays of vectors. The flattened one-dimensional vector array generated is given to the CNN for training, validation, and testing. From the original dataset, 80% or 90% is considered for training and validation whereas, the remaining 20% or 10% is taken for the testing. Out of 1068 images, 600 images and 100 images are accustomed to training and validation, and approximately 214 images are given testing.

The confusion matrix will give the total number of accurate detection and false detection in the matrix form. The detection accuracy and losses are calculated by the accuracy formula shown in the next section, and the confusion matrix calculates misdetection. The max-pooling layer plays an essential role in the CNN, which removes the newly generated unwanted features. Due to the similarity and redundancy of the images, sometimes overfitting will occur. Likewise, the thermal image also has the same characteristics; that is why image processing like HOG and image segmentation on top of HOG is interpreted with this machine learning algorithm (CNN) [15]. This interpretation will increase the performance of the machine learning algorithm. The probability function is used for the detection of animals in CNN. Binary cross-entropy is used to calculate the loss in detection, also labels 0 and 1 are assigned with and without deer.

IV. Results and Discussion

The experimental study and the proposed solutions are discussed in this section. The pictorial, tabulation, and matrix representation give details about the outputs generated. Finally, the confusion matrix will expose the detection accuracy, and loss.

A. *Test Setup*

This section describes the challenges and difficulties faced during the data collection processes and the simulation procedure. To avoid accidents, identifying the high accuracy detection system on the roadside due to the wildlife animals is proposed in this paper. FLIR ONE Pro, a high-definition thermal camera, is used for data collection. The authors collect the data during the nocturnal period along the highway and roadside pavements. The dataset will have diversified images, and also, without deer images will present to check the detection.

Data collection was performed every night for three continuous weeks in May 2019 and in November 2020 in the San Antonio area in Texas, USA. During data collection, the challenges faced are rainy nights, animal distraction, and hibernation. All the images in the dataset are in JPEG format, and primarily the data are collected from the forest side areas (near highways). The images are taken from the driving vehicle to check the complexity of the network used for testing.

B. Model Parameters

Table I. shows the sample model of the network for three convolution layers with a filter size of 256 and one global max-pooling layer, and finally, the dense layer, which is used to flatten the vector value of the detected features.

TABLE I. SAMPLE MODEL PARAMETERS WITH SPECIFICATION FOR IMAGE SEGMENTATION + HOG-CNN & HOG-CNN

Layer (type)	Output Shape	Param #
conv1d_1 (Conv1D)	(None, 2696, 256)	4096
conv1d_2 (Conv1D)	(None, 2692, 256)	327936
conv1d_3 (Conv1D)	(None, 2688, 256)	327936
global_max_pooling1d_1 (Glob	(None, 256)	0
dense_1 (Dense)	(None, 1)	257

Total params: 660,225
Trainable params: 660,225
Non-trainable params: 0

The total parameters are both trainable and non-trainable parameters, the features of the dataset given to the machine learning network.

C. Result Analysis

The result analysis describes all the inputs and comparison outputs of the existing and proposed intelligent system. From the dataset, one sample image is shown in Fig. 9. Moreover, the edge-based image segmentation output and the HOG outputs are shown in Fig. 9. and Fig. 10.

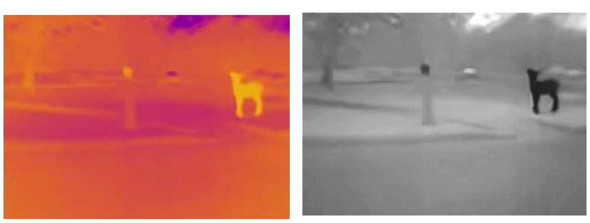

Fig. 9. Resized and Cropped Thermal and Edge-based Image Segmentation images

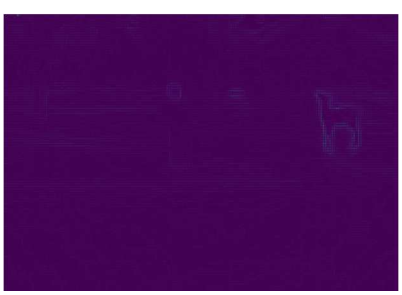

Fig. 10. HOG output image

Fig. 10. shows the segmented image of the same dimension, as the original image respectively. The image processing feature extraction is used to extract the informative feature of the given input image. The dimension of the images is converted into 128x128, by which the performance will be faster than the original image size. It takes around 10 to 20 seconds for each iteration or epochs; the existing systems take 40 to 50 seconds for the proposed model for training and validation. The testing will take milliseconds for one activation layer and a few seconds for two activation layers in the model. The proposed model, like image segmentation + HOG-CNN, will consume more time when compared with the existing HOG-CNN intelligent system [2][3].

The device setup used for the complete training, validation, and testing is MacBook Pro with specifications as follows,

- Processor 2.3 GHz Dual-Cor Intel Core i5.
- Memory 8 GB 2133 MHz LPDDR3.
- Graphics Intel Iris Plus Graphics 640 1536 MB.

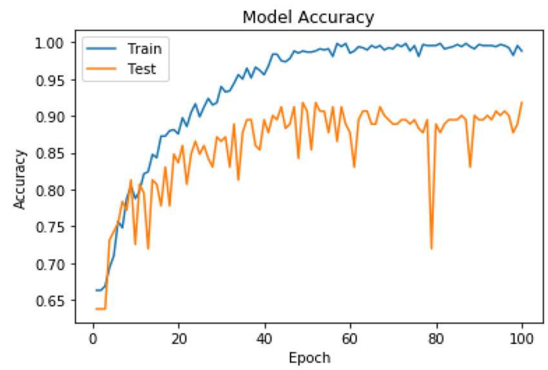

Fig. 11. HOG - CNN Model accuracy of the training and validation dataset for 100 epochs

The model accuracy of the existing HOG-CNN network is shown in Fig. 11. The training and testing variation in the accuracy is determined, and the pictorial representation is seen clearly. The testing gives around 90% of accuracy, as shown in the graph.

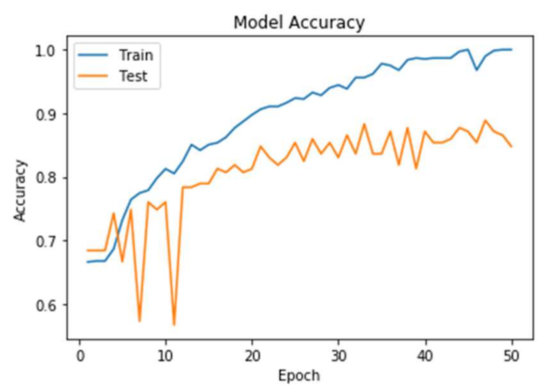

Fig. 12. Image Segmentation + HOG - CNN Model accuracy of the training and validation dataset for 50 epochs

Fig. 12. shows the proposed image segmentation with the HOG -CNN accuracy model. The x-axis will have the number of epochs, and the y axis gives the percentage. The accuracy percentage for the proposed model is around 85% maximum and 65% minimum. Even though the training accuracy reaches

the maximum, the testing produces about 80% - 85 % detection of the given image dataset.

$$\text{Accuracy} = \frac{\text{True Positive+True Negative}}{\text{Total}} \quad (3)$$

The above equation (3) is used to calculate the accuracy of the machine learning algorithm.

TABLE II. COMPARISON OF TESTING ACCURACY FOR BOTH EXISTING HOG-CNN AND IMAGE SEGMENTATION+ HOG-CNN FOR 5 RUNS

S. No.	Proposed System	Testing Accuracy	Avg.	Max.	Min.
1.	Image Segmentation + HOG-CNN	85%	77%	85%	63%
2.		73%			
3.		63%			
4.		82%			
5.		83%			
1.	HOG-CNN (Existing)	90%	90%	91%	89%
2.		90%			
3.		90%			
4.		91%			
5.		89%			

Table II gives the testing accuracy of both the existing and proposed systems. The splitting of the dataset for the training testing and validation will be random. In the table total of five tests are conducted for both the intelligent system model. The existing system was also tested because of comparison purposes. The percentage values are rounded off to the nearest integer. The average value will be 90%, the maximum and minimum will be 91% and 89% based on the detection for the existing HOG-CNN system. The proposed intelligent system produces testing accuracy of average 77%, a maximum of 85%, and a minimum of 63%, which is not the expected accuracy compared with the Existing model. The image segmentation on top of the Hog will increase the detection for the RGB images. However, for the thermal image, the accuracy of the image segmentation with HOG-CNN produces less percentage.

Fig.13. proves the variations of testing accuracy in percentage for all five times with different 50 and 100 epochs. Here both the existing and proposed models are compared in the bar chart. The blue color defines the accuracy of the proposed intelligent system, and the orange color represents the accuracy percentage of the existing system. The bar chart clearly shows that the image segmentation on top of the HOG did not increase the accuracy of the machine learning algorithm. In all five tests, the image segmentation with the HOG-CNN produces less accuracy percentage. Combining two image processing techniques like HOG and edge-based image segmentation will not increase the efficiency of animal detection.

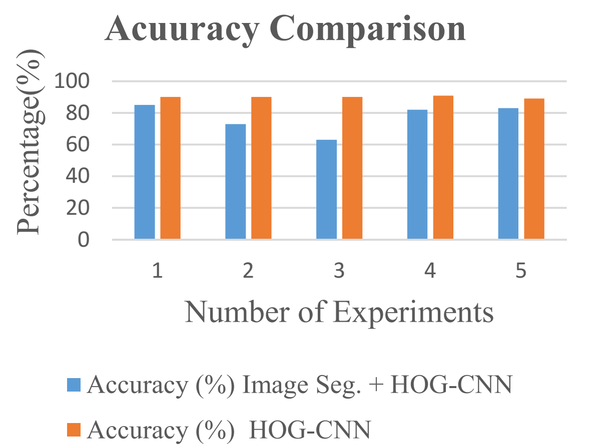

Fig. 13. Bar chart Testing Accuracy for ten times - 100 epochs

TABLE III. COMPARISON OF DETAILED TESTING ACCURACY FOR FIVE TIMES

S. No.	Proposed System	ACC.	CM	TP	TN	FN	FP
1.	Image Seg. + HOG-CNN	85%	[[53 21] [11 129]]	129	53	11	21
2.		73%	[[20 42] [15 137]]	137	20	15	42
3.		63%	[18 44] [34 118]]	118	18	34	44
4.		82%	[[60 14] [25 115]]	115	60	25	14
5.		83%	[[60 14] [22 118]]	118	60	22	14
1.	HOG - CNN (Existing)	90%	[[48 14] [12 140]]	140	48	12	14
2.		90%	[[54 8] [13 139]]	139	54	13	8
3.		90%	[[51 11] [10 142]]	142	51	10	11
4.		91%	[[54 8] [12 140]]	140	54	12	8
5.		89%	[48 14] [9 143]]	143	48	9	14

Table III shows the detailed split-up of the confusion matrix obtained as the output of the whole process. The tabulation includes the accuracy(ACC.), confusion matrix (CM), true positive (TP), true negative (TN), false positive (FP), false negative (FN). The input taken as an input for both the intelligent system is the same. The convolution layers, kernel size, and filters used for both systems are the same. The activation function used in both the intelligent system model is Rectified Linear Unit (ReLu), which increases the performance of the probability measurement system. The percentage generated by the proposed method is 85%, 73%, 63%, 82%, and 83% testing accuracy.

Table IV shows the output of the whole system model. An example is given below for one time 50 epoch. From the confusion matrix, both the false positive (FP) and false-negative (FN) is misdetections in the proposed system. Out of 214 testing images, 193 images are considered good detection, and the remaining 21 images are considered misdetection.

TABLE IV. EXAMPLE OF CONFUSION MATRIX (CM)

Confusion Matrix
[[51 11]
[10 142]]
True Positive – 142 (Animal Detected as yes)
True Negative – 51 (Animal Detected as no)
False Negative – 10 (False Detection as no)
False Positive – 11 (False Detection as yes)

The actual positive (TP) 142 images imply the animal is detected as "YES," and true negative (TN) 51 images indicate no animal is detected as "NO." The remaining 21 images are seen as false positives, and false negatives are called animals' misdetection. The accuracy percentage is calculated by using equation (3).

V. CONCLUSION

Image segmentation combined with HOG transformation and CNN functional prototype has proven its eminence in wildlife detection using the thermal image for the image detection in the animal-vehicle collision. As a result, the existing HOG transformation with CNN produces 91% of testing accuracy; however, the proposed edge-based image segmentation with Hog transformation and CNN makes a maximum of 85%. The comparative study has proven that the HOG with CNN produces more accuracy than the proposed intelligent system. Hence it is proved that the image segmentation over the HOG transformation neither enhances the detection percentage nor increases the accuracy. The Edge image segmentation is the most effective mode in image segmentation. The combination of HOG with Image segmentation will work only for the RGB images and is not adequate for thermal images due to unsatisfactory image boundary. In RGB, the images used for detection come without intensity inhomogeneity, but the characteristics of the thermal image come with no contour and boundary leakage problems. The images captured at nighttime increase the complexity of the detection. The combination of HOG and CNN produces more effective results than the Image segmentation with HOG and CNN. In this research exploration, the conclusion is integrated edge-based image segmentation, and HOG has not produced the desired result for thermal images. As the problem solution is time-sensitive, combining two image processing techniques is higher than the existing system. The future objective of this research is aimed to increase the testing accuracy percentage by replacing the segmentation types with threshold-based or region-based segmentation.

REFERENCES

[1] https://www.fhwa.dot.gov/publications/research/safety/08034/exec.cfm

[2] Munian, Y., Martinez-Molina, A., & Alamaniotis, M., Intelligent System for Detection of Wild Animals Using HOG and CNN in Automobile Applications. 2020 11th International Conference on Information, Intelligence, Systems and Applications (IISA, 1–8. https://doi.org/10.1109/IISA50023.2020.9284365, 2020.

[3] Munian, Y., Martinez-Molina, A., & Alamaniotis, M., Design and Implementation of a nocturnal animal detection intelligent system in Automobile Applications. International Conference on Transportation and Development 2021 – Transportation operations technologies and safety (pp. 438 – 449), American Society of Civil Engineers (ASCE), https://ascelibrary.org/doi/10.1061/9780784483534.038, 2021.

[4] Socarrás Salas, Y., Vázquez Bermudez, D., López Peña, A. M., Gerónimo Gomez, D., & Gevers, T., "Improving HOG with image segmentation: Application to human detection". Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 7517 LNCS(January), 178–189. https://doi.org/10.1007/978-3-642-33140-4_16, 2012.

[5] Chen, Y. Y., Chen, W. S., & Ni, H. S., "Image segmentation in thermal images." Proceedings of the IEEE International Conference on Industrial Technology, 2016-May, 1507–1512., https://doi.org/10.1109/ICIT.2016.7474983, 2016.

[6] Ahmed, I., Ahmad, M., Khan, F. A., & Asif, M., "Comparison of deep-learning-based segmentation models: Using top view person images." IEEE Access, 8, 136361–136373. https://doi.org/10.1109/ACCESS.2020.3011406, 2020.

[7] Alhindi, T. J., Kalra, S., Ng, K. H., Afrin, A., & Tizhoosh, H. R., "Comparing LBP, HOG and Deep Features for Classification of Histopathology Images." ArXiv,2018.

[8] Duarte, A., Carrão, L., Espanha, M., Viana, T., Freitas, D., Bártolo, P., Almeida, H. A., "Segmentation Algorithms for Thermal Images". Procedia Technology, 16, 1560–1569., https://doi.org/10.1016/j.protcy.2014.10.178, 2014

[9] Dilpreet, K., & Yadwinder, K., "Various Image Segmentation Techniques: A Review." International Journal of Computer Science and Mobile Computing, 3(5), 809–814. Retrieved from www.ijcsmc.com, 2014

[10] Liu, X., Deng, Z., & Yang, Y., "Recent progress in semantic image segmentation." Artificial Intelligence Review, 52(2), 1089–1106. https://doi.org/10.1007/s10462-018-9641-3, 2019.

[11] Shaikh, S., Gite, H., Manza, R. R., Kale, K. V., & Akhter, N., "Segmentation of thermal images using thresholding-based methods for detection of malignant tumours." Advances in Intelligent Systems and Computing, 530, 131–146. https://doi.org/10.1007/978-3-319-47952-1_11, 2016.

[12] Li, C., Xia, W., Yan, Y., Luo, B., & Tang, J., "Segmenting objects in day and night: Edge-conditioned CNN for thermal image semantic segmentation." ArXiv, 1, 1–12., 2019.

[13] Liang, Y., Wang, L., & Zhang, L., "Infrared image segmentation using HOG feature and kernel extreme learning machine." AOPC 2015: Image Processing and Analysis, 9675(May), 96751B. https://doi.org/10.1117/12.2199352, 2015.

[14] Manda, M. P., & Kim, H. S., "A fast image thresholding algorithm for infrared images based on histogram approximation and circuit theory." Algorithms, 13(9). https://doi.org/10.3390/A13090207, 2020.

[15] Minaee, S., Boykov, Y. Y., Porikli, F., Plaza, A. J., Kehtarnavaz, N., & Terzopoulos, D., "Image Segmentation Using Deep Learning: A Survey." IEEE Transactions on Pattern Analysis and Machine Intelligence, 1–22. https://doi.org/10.1109/TPAMI.2021.3059968, 2021

[16] Qiao, Y., Wei, Z., & Zhao, Y., "Thermal infrared pedestrian image segmentation using level set method." Sensors (Switzerland), 17(8). https://doi.org/10.3390/s17081811, 2017.

[17] https://www.python.org/downloads/release/python-360/