Enhancing the Real-Time Object Detection Using Fuzzy Boundary Detection in Image Segmentation

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Abstract **- Real-time object detection is one of the fundamental tools in computer vision applications, which range from surveillance operations to autonomous vehicles and robotic systems. The biggest challenge in object detection is accurate object detection and segmentation in cluttered dynamic environments that experience obscurations and lighting changes as well as scale changes. The presented work introduces fuzzy boundary detection that enhances the accuracy of object segmentation techniques to overcome the existing limitations in detection. The model is able to obtain a better edge definition for objects using the application of fuzzy c-means clustering which enhances its capability to separate objects from environmental noise. The pixel-level classification also becomes more accurate through this method because it applies fuzzy membership degrees to pixels that help in accurately identifying complex object boundaries. The performance level of the model gains significant improvements with both segmentation and classification operations when integrated with YOLOv5 object detection. The proposed model outperforms the baseline YOLOv5, along with other models, with the improvement of detection and segmentation accuracy due to better precision metrics that include mAP from 90.2% to 94.6%, mAP@0.5:0.95 from 79.1% to 85.4%, and IoU from 87.6% to 91.4%.**

Keywords: **Object Detection, Image Segmentation, Fuzzy Boundary Detection, YOLOv5 model.**

I. INTRODUCTION

Real-time object detection denotes the capacity to identify and locate items within a continuous data stream. The foundation of real-time object detection arises from the growing need for effective and precise interpretation of visual input in practical situations. Object detection is essential in several prominent sectors and is of significant relevance in different domains, including robotic navigation, virtual reality, robotics, and healthcare diagnosis [1]. Object detection is extensively used in several computer vision applications, such as autonomous driving, robotic vision, smart transportation, quality control in industrial inspection, and monitoring of objects. Two-stage models often provide greater efficiency. This resource-intensive network hinders the adoption of practical applications. To address this issue, fuzzy border detection is used to create extremely efficient object detecting systems. The analysis and comprehension of footage is a dynamic area of study. Numerous applications within this study domain, including video monitoring [2], optical recording of motion [3], applications for multimedia [4], video segmentation of items [5], and video coding [6], need the first detection of moving objects within the picture. The fundamental process required is the differentiation of dynamic entities, referred to as the foreground, from the static elements known as the backdrop. The primary method used is removing background information.

Real-time object detection in image segmentation benefits from fuzzy boundary detection since it enhances accuracy when segmenting objects showing ambiguous or overlapping boundaries. Detection of objects using traditional boundary techniques fails at times if the boundaries in the images are not clear, especially when such images contain low contrast and physical noise. The fuzzy boundary detection method solves the problem by allowing membership values of pixels instead of binary classifications that provide soft transitions between object and background elements [7]. It adds significant value to picture processing tasks that demand accurate border detection, such as medical imaging as well as remote sensing and automated inspection systems. Medical image processing suffers from bottlenecks during segmentation that is an essential requirement for higher-level image analysis but persists as a research problem that needs to be solved [8]. Parametric resolution limitations along with device bias fields and subject motion lead to inaccurate image data that produce artifacts involving noise and edge blurring and shading effects most notably in MR images.

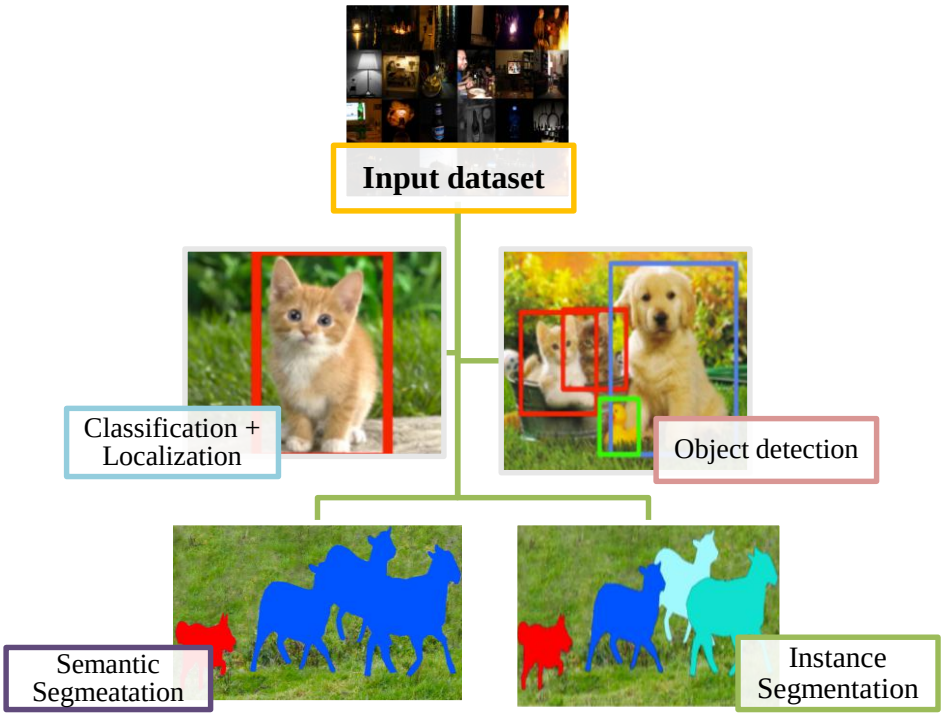

Figure 1: Object detection and segmentation

Fuzzy Parametric Classification

Fuzzy logic has been used in several domains over the last few decades. Its recognition is often linked to fuzzy clustering or the use of fuzzy based on if systems as classifications. Despite being a relatively recent theory, fuzzy logic has many applications, including process control, management, and decision-making. Nonetheless, for the objectives of this study, the most critical applications are to pattern recognition and classification. Targeting binary solutions is inadequate; the notion of membership, introduced [9], has developed as an innovative method to problem-solving. The membership rate is a mathematical value that measures the degree of an element's affiliation with a fuzzy set. The principal advantage of this theory is its capacity to articulate challenges using linguistic ideas instead of depending on exact numerical values to convey connections.

In fuzzy classification, each pixel is given a value that indicates its degree of membership to each conceivable category (such as a land cover class) within the area of interest (such as urban areas). The grade indicates the degree of association between the pixel and its designated land cover class, known as the “Fuzzy Membership Value” (FMV) [10]. The FMVs partly illustrate the land covering configuration of a hybrid pixel, allowing a more accurate and realistic representation of land covers. This method addresses several assumptions inherent in traditional classification [11]. FMVs may be acquired by the use of several classification models, such the fuzzy c-means method [12]. Real-time performance in fuzzy boundary detection methods requires the combination of optimization techniques including adaptive thresholding and multi-scale analysis with efficient computational models. Dynamic boundary refinement through these methods improves segmentation [13] accuracy while maintaining levels of computational efficiency. Applications in real-time segmentation become possible through the deployment of hardware acceleration and parallel processing methods that shorten latency times [14]. When fuzzy logic couples with advanced image processing techniques it yields reliable detection of objects due to changing environmental conditions.

This research aims to focus on real-time object detection by means of fuzzy boundary detection for image segmentation since it overcomes issues pertaining to the blurry and overlapped object boundaries under dynamic and noisy conditions. There is interest in this research as it needs the enhancement of the precision as well as speed of object detection systems working in fundamental domains, like autonomous vehicles and medical imaging as well as surveillance. The research integrates fuzzy logic applications with boundary detection techniques as a method to process image data uncertainty and imprecision patterns.

Innovative methods developed by the paper increase the accuracy of object detection with preservation of real-time processing capabilities. The main objectives of the research are as follows:

- To improve the accuracy of object detection and thus enhance by integrating fuzzy boundary detection with the YOLOv5 model.
- To minimize false detections and enhance precision-recall performance using fuzzy membership functions and fuzzy c-means clustering for the refinement of boundary definition in image segmentation.
- To analyze the effect of fuzzy boundary detection on detection speed and computational efficiency, balancing improved object recognition with real-time processing constraints.
- To analyze the proposed model's performance on objects at varying sizes, such as small, medium, and large, in comparison with the baseline YOLOv5 model and the previous model described in literature.

The research outlined is articulated as follows: Section 2, titled "Literature Survey," presents a summary of the existing studies in the area via a literature assessment; Section 3,"Research Methodology," articulates the suggested system, including full explanations of its stages and Section 4 "Result and Evaluation" offers an in-depth analysis of the performance of the suggested model, citing its suitability for object detection through comparative analysis with current method followed with conclusion.

II. REVIEW OF LITERATURE

New advances in fuzzy logic combined with optimization methods and hybrid methodologies produce significant improvements in image segmentation along with object detection precision. Researchers at *Ahmed et al. (2024) [15]* developed a system integrating Gaussian filtering with Fuzzy C-Means segmentation and saliency mapping under Genetic Algorithms to deliver successful dataset classification results. The Fuzzy-NMS module developed by *Wang et al. (2024) [16]* enhances multiple NMS-based detectors through its ability to refine boxes through volume and clustering density assessment. A distributed Edge-Cloud collaborative framework with fuzzy neural network task allocation developed by *Yuan et al. (2024) [17]* proved better than conventional edge and cloud computing systems. Numerous research studies attest to the fact that fuzzy logic demonstrates its ability to enhance segmentation with detection optimization through the reduction of noise and uncertainty levels.

Many studies have analyzed the development of new segmentation accuracy improvements based on adaptive learning method-based research integrating multi-level feature aggregation techniques. *Wen et al. (2023) [18]* designed a boundary extraction module that was able to effectively solve pixel boundary confidence problems in improving salience prediction results. A fast fuzzy C-Means clustering system coupled with Porter–Duff composition enables *Nawaz et al. (2023) [19]* to differentiate important objects from background noise. *Jawdekar et al. (2023) [20]* conducted research and developed deep learning-based CNNs using fuzzy inference rules for image denoising and edge detection and obtained more desirable results as opposed to histogram-based traditional paradigms. An updated version of the fuzzy Prewitt technique for image preprocessing was conducted in the research carried out by *De et al. (2023) [21]* , where payload detection steganography tasks successfully took place using high accuracy and F1-score performance metrics. Several studies have shown how fuzzy preprocessing with feature aggregation techniques improves the robustness of segmentation and efficiency of object detection.

Fuzzy clustering and metric-based segmentation techniques have witnessed further developments in handling multiple problems related to image processing. Edge thickness control with fuzzy rule-based methods was demonstrated by *Kumawat et al. (2022) [22]* as they integrated fuzzy logic with feature-based image registration. Low-rank representation by *Song et al. (2022) [23]* in conjunction with fuzzy clustering resulted in enhanced segmentation results based on optimizing data point relationship. *Ralevic et al. (2022) [24]* developed novel fuzzy metrics by combining aggregation functions with t-norms to improve segmentation accuracy. In *Xu et al. (2022) [25]*, researchers designed a Hidden Markov Model-based fuzzy C-Means clustering process against noise and *Chakraborty et al. (2022) [26]* developed an unsupervised segmentation protocol on type-2 fuzzy frameworks for the study of radiological images in

COVID-19 cases. This helps in edge detection and object segmentation as *Versaci et al. (2021) [27]* and *Jalal et al. (2021) [28]* combined this fuzzy divergence with the entropy minimization technique. The performed studies illustrate how fuzzy logic works efficiently with clustering algorithms, feature extraction techniques along with classification operations as well, and it reflects its significance in the contemporary frameworks of image processing.

Research Gap

Despite significant advances made in fuzzy logic-based image segmentation and object detection, some problems still persist. The existing approaches consisting of Fuzzy C-Means clustering and Fuzzy-NMS as well as fuzzy-enhanced CNN preprocessing have demonstrated improved capabilities in object segmentation and target detection more reliably. The current methods are mostly focused on improving the segmentation precision but not boundary inconsistencies in real-time detection conditions. Coupling boundary extraction modules along with the fuzzy inference rules improves the saliency detection results with edge refinement; however, its deployment is still an open challenge for real-time object detection systems. The research requires an optimized fuzzy boundary detection mechanism because it should enhance real-time object detection through improved boundary precision along with improved segmentation accuracy at reasonable computational speeds.

III. RESEARCH METHODOLOGY

The research introduces a novel framework for object detection using fuzzy boundary detection. The proposed methodology has four distinct phases: data processing, feature extraction, classification model, and evaluation matrix for proposed models. Figure 2 visually illustrates these steps.

A. Dataset Description

The MS COCO (Microsoft Common Objects in Context) establishes itself as one of the leading benchmark datasets that support object detection and segmentation along with image captioning activities [29]. The database holds over 1.5 million object examples that are spread over 80 distinct categories within the 330,000 images present in it. The dataset holds object bounding boxes with segmentation masks and keypoint detection annotations enabling multiple computer vision applications for analysis. MS COCO has diverse real-world complex environments displaying the presence of more than one object along with full object blockages and varied camera point-of-view positions along with different lighting conditions. MS COCO is the default benchmark for object detection and segmentation algorithms due to its variety of objects together with the thoroughness in the quality of annotation.

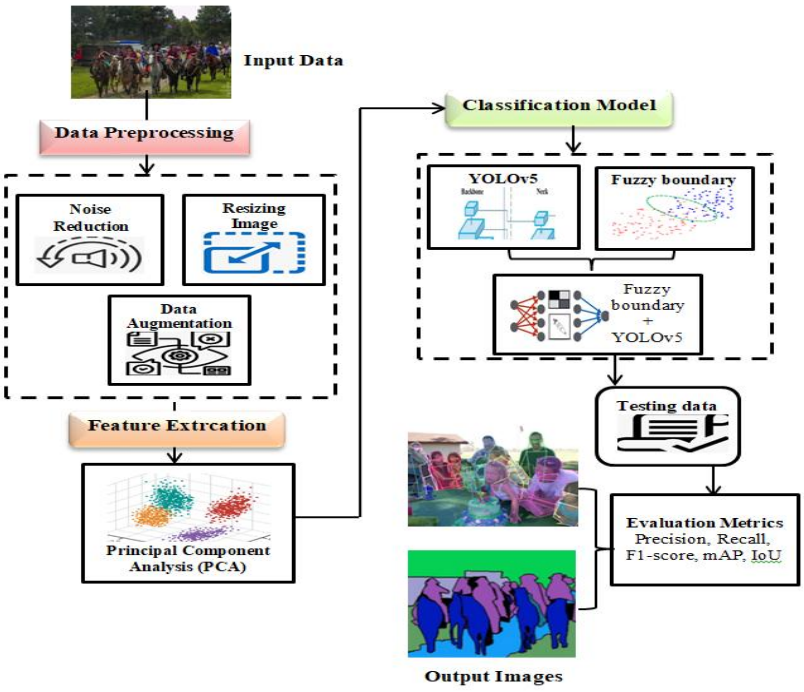

Figure 2: Proposed framework

B. Data preprocessing

Data processing is a crucial element for trustworthy discoveries in real time object detection.

- Noise Reduction

Noise negatively affects the precision of real-time object detection during open and shade environments while capturing images [30]. Fuzzy boundary detection techniques function to remove noise-related errors through enhancement of object edges that decrease wrong classification of the target objects. Noise ruins the fidelity of the image using the following mathematical model:

$$J(u) = \frac{I(u) - A(1 - t(u))}{t(u)} \qquad (1)$$

The observed image I(u) is produced by the true scene radiance J'(u) altered by transmission t(u) and atmospheric light element A, and noise distortion affects the process as n(u). The system utilizes fuzzy membership functions in combination with fuzzy c-means clustering to enhance boundary detection so that it can distinguish authentic object edges from artifacts created by noise disturbances. The proposed method improves object detection performance while working under low-contrast conditions or complicated scenarios hence bringing about enhanced accuracy in segmentation and reduced incorrect detection:

$$I(u) = J'(u)t(u) + A\big(1 - t(u)\big) + n(u) \qquad (2)$$

Equation (1) may be resolved in accordance with the newly introduced noise delineated in (2).

- Resizing images

The upload of all data into memory presented many obstacles in this investigation. The issue was resolved by processing the data in batches. The processed data consist of identical photos captured by the camera, which were transformed into framed images then utilized as the network's intake.

Image scaling is an essential process in machine vision for object identification since it facilitates expedited training of proposed models. During this phase, all photos are downsized to a uniform dimension of 416, using a batch size of 32 for the purpose of training. Standardize all images to a consistent dimension, frequently 416x416 or 608x608 pixels, to ensure consistency.

- Data Augmentation

To enhance the extrapolation of the YOLOv5 model and empower it to manage diverse real-world circumstances, we used several augmentation strategies during training. These augmentations enable the simulation of diverse ambient conditions, illumination fluctuations, and object rotations. The subsequent augmentations were used:

Rotation (degrees): Pictures were periodically rotated within a defined degree range to enhance the model's capacity to identify items from various angles.

$$P' = rotate(P, \theta) \qquad (3)$$

where $\theta \in [-180^\circ, 180^\circ]$ denotes the randomly chosen rotation angle.

Translation (translate): The picture was moved both horizontally and vertically by a portion of its dimensions, imitating partial sight of items, which is crucial for identifying things that may not be entirely visible in real-world situations.

$$P'(u', v') = P(u + t_u \cdot w, v + t_v \cdot h) \qquad (4)$$

Where t_u, $t_v \in$ [-0, 1, 0.1], h and w represent height and width of the image.

Scaling (scale): The picture was enlarged by a gain factor to replicate items at differing ranges from the camera, assisting the model in detecting things of diverse sizes.

$$P'(u', v') = scale(P, \delta_s) \qquad (5)$$

Where δ_s =0.5 regiulates the scaling factor

C. Feature Selection

Determine the specific spectrum bands or indexes that hold pertinent data for the desired classes. The feature choice procedure utilizes "Principal Component Analysis" (PCA) or rank-feature methods to identify the most important features while lowering dimensionality.

D. Classification Model

- YOLOv5 Model

The You Only Look Once (YOLO) technique is highly regarded for real-time object recognition. It employs YOLOv5, an enhanced iteration of YOLO. YOLOv5 is both fast and precise in comparison to its predecessor versions of YOLO [31]. Within the existing YOLOv5 framework, there are many unique variants: YOLOv5s, YOLOv5n, YOLOv5m, and YOLOv5x [32].

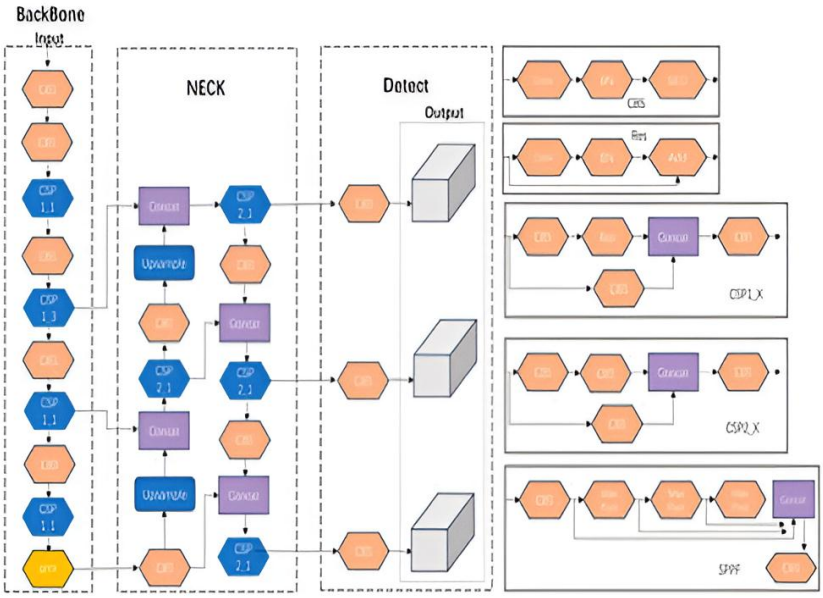

Figure 3: YOLOv5 network structure [33].

Figure 3 shows the YOLOv5 network structure. Among this collection of network models differing in scale, YOLOv5s is distinguished by its intentional network simplicity, designed for edge deployment to enable real-time object identification. Moreover, YOLOv5s offers significant benefits, such as enhanced detection stability, precision, and ease of deployment. The efficient interaction among these diverse elements enhances its notable performance. Adaptive anchor frame estimate and Mosaic data augmentation at the input stage are two of the several enhancements in YOLOv5.

- Fuzzy Boundary Detection

The "Fuzzy c-means" (FCM) approach was used in a supervised way to calculate the fuzzy memberships for each pixel. This method regards spectral values including several pixels in the region as data vectors. It then constructs a matrix (c×n), where c denotes the number of land cover categories and n signifies the length of data vectors, using what are referred to as class norms. This technique determines subscriptions based on the weighted closeness to the class means. However, the method no longer calculates the averages of the classes [34]. Consequently, a modified approach was used, and the groups were generated using the following equation 6.

$$\mu_{ik} = \left[\left(\frac{1}{d_{ik}^2}\right)^{\frac{1}{m-1}}\right]\left[1/\sum_{j=1}^{c}(1/d_{ik}^2)^{1/(m-1)}\right] \quad (6)$$

Fuzzy Membership Function Design

The surface area data for the specified bands were combined using fuzzy operators such as fuzzy least fuzzy maximum, flexible algebraic goods, fuzzy logical sum, and fuzzy gamma operators.

When dealing with the fuzzy portrayal of a remotely detected appearance, land use-cover groupings can be accurately defined as fuzzy sets, where pixel values act as elements of these sets. Every pixel, which is a mixture of multiple colors, is given a set of definition grades that indicate the degree to which its value is related to various classes.

- Triangular Membership Function (TMF)

Let p, q, and r represent the x-coordinates of the three vertices of the fuzzy set A, where 'p' denotes the lower boundary, 'r' signifies the upper boundary with an affiliation degree of zero, and 'q' indicates the center with an affiliation degree of one.

$$F_A(x) = \begin{cases} 0 & , \quad if\ x \le p \\ \frac{(x-p)}{(q-p)} & , \quad if\ p \le x \le q \\ \frac{(r-x)}{(r-b)} & , \quad if\ q \le x \le r \\ 0 & , \quad if\ x \ge r \end{cases} \quad (7)$$

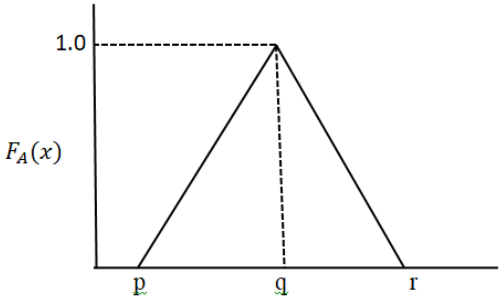

Figure 4: TMF for fuzzy membership classification

Proposed Mixed Pixel Classifier

Per Pixel Identification is a technique that considers each pixel as an isolated entity, supposing it encompasses just one cover type or class. This method is often known as a conventional separator. This study use fuzzy membership to tackle the problem of blended pixels in various image classifications, known as the fuzzy method.

E. Evaluation Matrices

This section assesses the efficacy of the proposed DL model. The suggested methodology utilizes a model to evaluate the precision of SDP. The assessment framework has four components: True Negative (TN), False Negative (FN), True Positive (TP), and False Positive (FP). The model's efficacy was assessed, where $A_{accuracy}$, $F1_{score}$, $P_{precision}$, and R_{recall} are the relevant variables:

$$\text{Accuracy} = \frac{\text{TN+TP}}{\text{TP+FN+FP+TN}} \quad (13)$$

$$\text{Precision} = \frac{\text{NA}}{\text{NA+FP}} \quad (14)$$

$$\text{Recall} = \frac{\text{NA}}{\text{FN+NA}} \quad (15)$$

$$\text{F1 score} = \frac{2\times\text{precision}\times\text{recall}}{\text{recall+precision}} \quad (16)$$

$$mAP = \frac{1}{n}\sum_{i=1}^{i=n} AP_i \quad (17)$$

Where n is an object class in this problem. AP_i stands for Average Precision for class i, which can be calculated using the integrals of the PR curve.

$$IoU = \frac{Area\ of\ overlap}{Area\ of\ union} \quad (18)$$

A higher IoU indicates better object localization. Commonly, an IoU threshold of 0.5 is used for a correct detection.

IV. RESULT AND EVALUATION

A. Quantitative Evaluation

Qualitative evaluation of the proposed model shows that it enhances real-time object detection using the integration of fuzzy boundary detection with YOLOv5. The outcomes of segmentation are thus enhanced with this enhancement, particularly in demanding situations. As illustrated in Figure 5, the baseline YOLOv5 model detects 950 true positives along with 50 false negatives and 55 false positives then 945 true negatives; however, the suggested YOLOv5 variant with fuzzy boundary detection has reached 970 true positives and 30 false negatives along with 30 false positives and 970 true negatives.

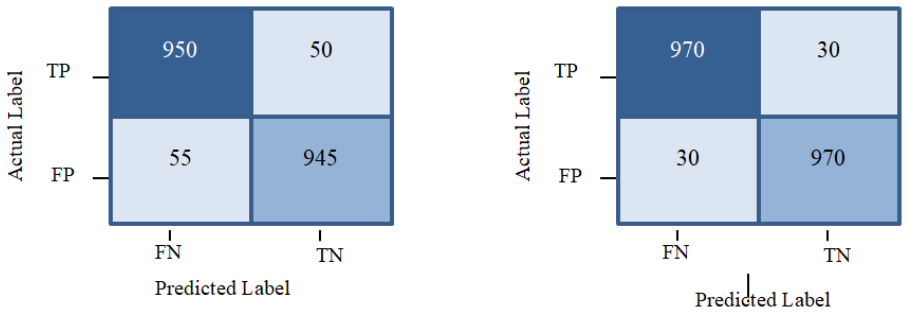

Figure 5: Confusion matrix of baseline YOLO model and YOLO + Fuzzy boundary model, respectively.

Table 1 indicates the success of integrating fuzzy boundary detection with YOLOv5. The proposed model outperforms the baseline system at all measurement points by achieving enhanced mAP along with increased precision and recall values and an increased F1-score. The system detected abilities were improved significantly because, from 90.2% to 94.6%, mAP@0.5 rose while mAP@0.5:0.95 increased to 85.4% from 79.1% across different IoU thresholds. The performance benefits precision with recall better object detection and fewer incorrect predictions by the system. The IoU measure showed superior segmentation accuracy because it increased from 87.6% to 91.4%. Results from research highlight how fuzzy boundary detection techniques successfully improve the classification of objects process.

Table 1: The performance comparison between YOLOv5 and YOLOv5 combined with Fuzzy Boundary Detection across the key evaluation metrics

Metric	YOLOv5 (Baseline)	YOLOv5 + Fuzzy Boundary Detection (Proposed)
mAP@0.5	90.2%	94.6%

mAP@0.5:0.95	79.1%	85.4%
Precision	93.5%	95.2%
Recall	92.1%	94.8%
F1-Score	92.8%	95.0%
IoU (Intersection over Union)	87.6%	91.4%

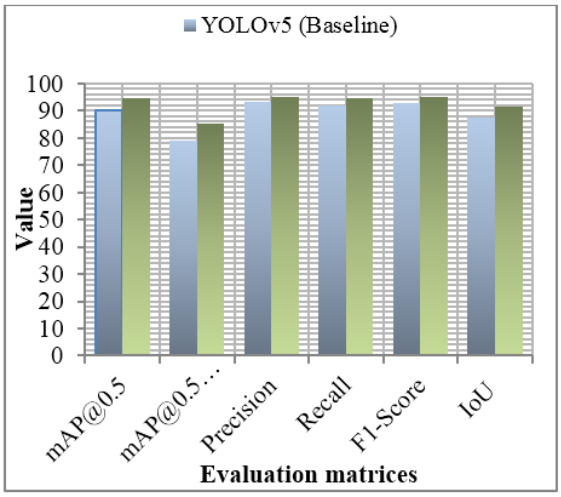

Figure 6: Visual representation of performance improvements in the proposed model over the baseline YOLOv5.

The performance metrics graphical illustrated in figure 6 depicts that the proposed model surpassed the YOLOv5 baseline. Model robustness along with detection and segmentation precision witnessed substantial improvements from the bar chart or line graph data presented below. This resulted in increased values of mAP and IoU metrics that prove enhanced location precision, as well as higher precision scores and F1-score rates, meaning better classification confidence.

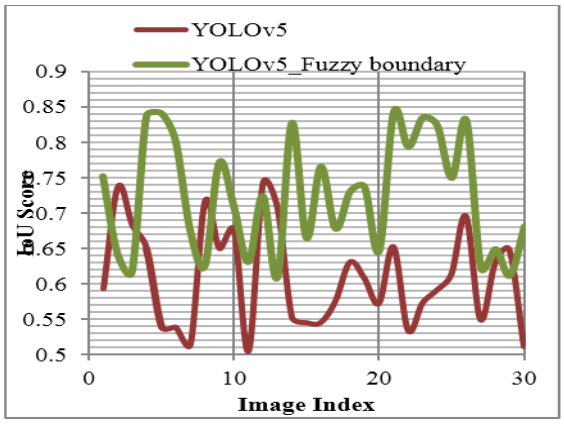

Figure 7: IoU score comparison between YOLOv5 and YOLOv5 with Fuzzy Boundary Detection across different image indices.

Figure 7 compares the IoU scores of YOLOv5 and YOLOv5 with fuzzy boundary detection across different image indices. The proposed model maintains green curve IoU scores above YOLOv5 baseline (red curve) across all conditions which proves superior object segmentation performance. The proposed model demonstrates excellent capability for improving object boundary detection by showing both high performance and stable outcomes which remain steady despite image complexity changes.

4.1 Detection Time Performance

The detection time performance evaluation compares the inference time and FPS of the baseline YOLOv5 and the proposed YOLOv5 with fuzzy boundary detection is illustrated in table 2. The baseline model achieves an inference time of 8.2 ms per image with a processing speed of 121.9 FPS, while the proposed model has a slightly higher inference time of 9.1 ms, resulting in a reduced FPS of 109.9.9. This incurs a small increase in computational cost due to the extra processing needed for the refinement of fuzzy boundaries.

Table 2: The inference time per image and the corresponding FPS

Model	Inference Time (ms)	FPS (Frames Per Second)
YOLOv5 (Baseline)	8.2 ms	121.9 FPS
YOLOv5 + Fuzzy Boundary Detection	9.1 ms	109.9 FPS

The percentages of false negatives from YOLOv5 baseline models in addition to YOLOv5 models utilizing fuzzy boundary detection across three object size classes are shown in table 3 below. The YOLOv5 + Fuzzy Boundary Detection model shows a marked reduction in false negatives higher than the baseline results. The precision of detection on small objects enhanced since the percentage of false negatives reduced from 17.9% to 10.5%. The detection rate increased for all object categories when YOLOv5 + Fuzzy Boundary Detection were used. The model resulted in 10.5% false negatives for small objects followed by 5.4% for medium objects and 2.0% false negatives for large objects, respectively. The model shows better detection capabilities for medium and small objects through recent improvements which make detection tasks easier for traditional systems.

Table 3: error rate analysis of proposed models

Category	YOLOv5	YOLOv5 + Fuzzy Boundary
Small Objects	17.9%	10.5%
Medium	8.6%	5.4%
Objects		
Large Objects	3.1%	2.0%

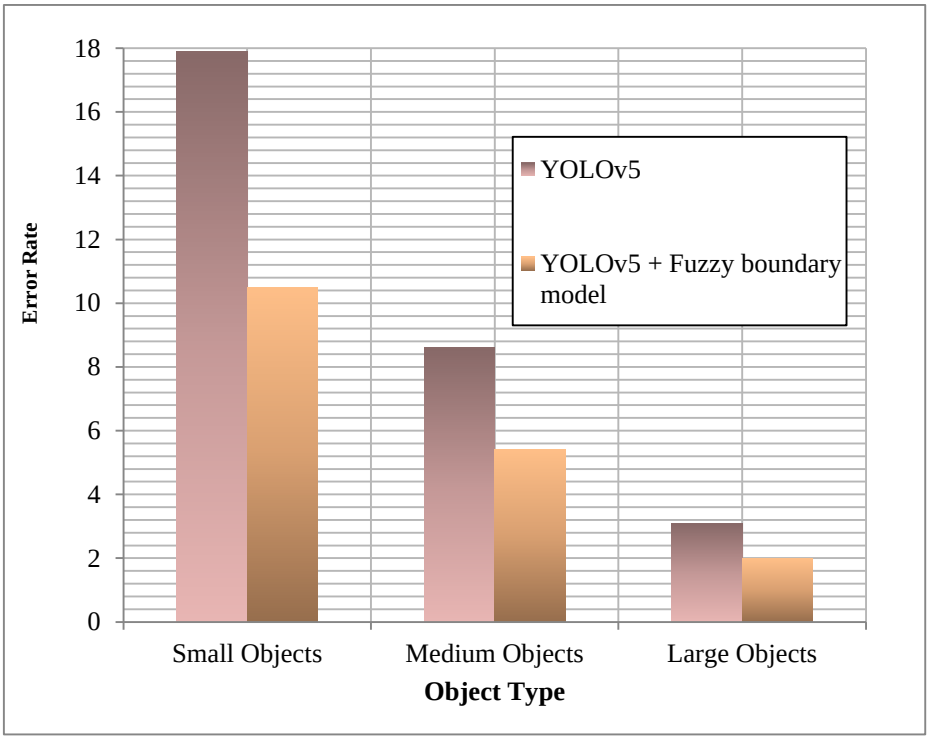

Figure 8: Error rate comparison for small, medium, and large objects using suggested models.

The figure 8 above presents error rates alongside baseline YOLOv5 depicted in dark brown. The YOLOv5 when using fuzzy boundary detection fuzzy boundary detection method proves useful for evaluation of small, medium, and large objects. advancing the recognition outcome of objects when The proposed model depicted in light brown identifying smaller objects, which normally present maintains lower error rates for each object size- more identification difficulties. including small ones and medium ones-than

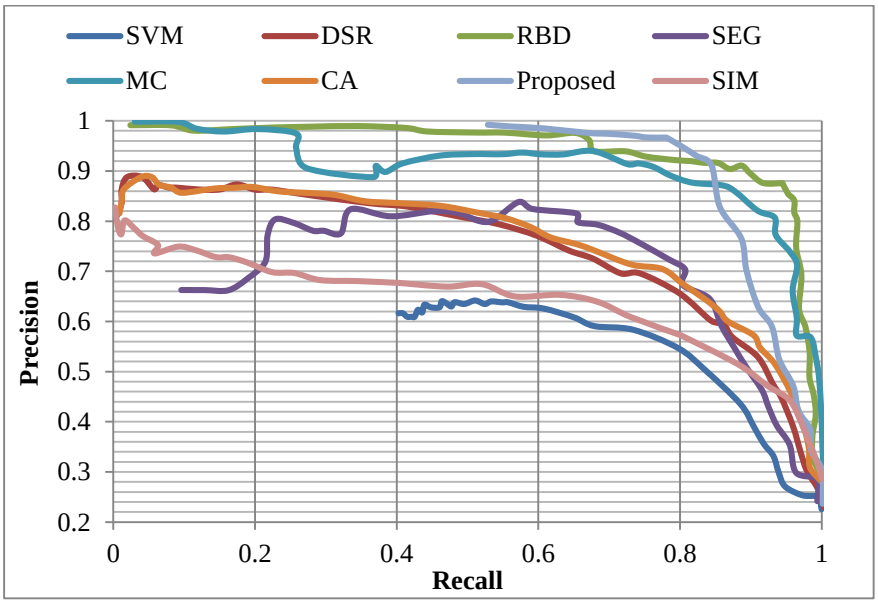

Figure 9: Precision-recall curve comparison of different object detection models, highlighting the superior performance of the proposed model

Figure 9 presents precision-recall curve creates a performance comparison system which includes SVM, DSR, RBD, SEG, MC, CA and SIM execution models and the proposed new model [35-39]. The model performs better than others because it achieves and sustains high precision at different recall points thus establishing effective detection accuracy control and system sensitivity. The RBD and SEG models demonstrate good results despite performing below the proposed solution. Precisions of SVM and SIM models fall sharply as the recall values have increased since the methods cause higher false positive detection results. The proposed method exhibits its ability to enhance the accuracy of detection along with maintaining stability for the varying recall metrics as the overall trend is encouraging.

Figure 10: Object detection using Fuzzy boundary with YOLOV5 model

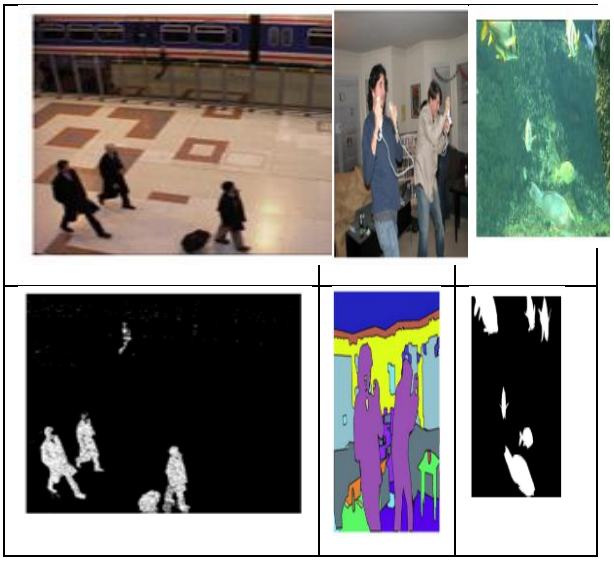

Figure 11: Image segmentation

The proposed model, which carries YOLO architecture with the ability of detection with fuzzy boundaries, enables effective working of functions for object detection and segmentation within figure 10 & 11 so that the objects can be effectively detected and, in turn, give descriptive labels for all people and vehicles appearing within the scene and skis. Precise boxes that reflect identification and classification abilities of various scene objects that demonstrate the proficiency of the model make it very effective even for the most complex visual scenes. Successful visual segmentation happens through the proposed model well, as demonstrated in the figure, where the objects are differentiated quite clearly from the gray background of the visual field. This segmentation method makes it possible to precisely identify objects even in challenging situations because it can effectively detect complex object edges. The fuzzy boundary detection system allows for the accurate definition of boundaries that function well under difficult context conditions.

V. CONCLUSION

The coupling of fuzzy boundary detection technology with YOLOv5 creates superior real-time object detection results in challenging operating conditions. Fuzzy c-means clustering enhances boundary delineation accuracy and object segmentation precision which leads to decreased errors during false positive and negative detections. The evaluation metrics indicate good performance gains demonstrating mean Average Precision (mAP) of 94.6% and mAP@0.5:0.95 reaching at 85.4% along with IoU 91.4%. The optimized ensemble produces precision with 95.2%, along with 94.8% recall rate and 95.0% F1-score. The proposed model is thus superior in performance compared to other models it has been compared against and therefore is the optimal solution for object detection and segmentation. The detection accuracy improvements justify this model as the best choice even though inference time has increased slightly. Further optimization analysis should be performed to reduce model cost-constraints while maintaining performance requirements and extend the model's usability towards various real-world detection and segmentation applications.

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