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Iot-Yolox: Comparative Evaluation And Advancement Of Object Detection Models For Iot-Based Robotic Arms

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Abstract—
The object and image detection capabilities emerging from IoT systems with robotic arms promote automation across healthcare institutions and agricultural settings and supply chain management as well as production facilities. Real-time decisions and robotic system intelligence depend on object detection since it serves as their primary essential foundation. A robotic system uses this detection process as part of its methodology to identify objects which allows robots to connect with objects around them. The implementation of advanced deep learning object detectors in IoT environments becomes challenging because of constrained memory resources combined with limited computing capability and restricted bandwidth and necessary time-sensitive operation requirements.The study primarily investigates the relationship that exists between the performance capabilities of leading detection algorithms and IoT robotics computational boundaries. We have analyzed seven current object detection algorithms with YOLOv5, SSD, Faster R-CNN, MobileNet-SSD, EfficientDet, RetinaNet together with CenterNet. The evaluation framework analyzes seven object detection models through precision metric tests of mean Average Precision and speed metrics of frames per second as well as measuring model complexity by floating-point operations per second and energy efficiency parameters along with system memory consumption and response time during real-time operation. The included mathematical explanation accompanies architectural design specifications to explain function and application compatibility for each model.The project presents IoT-YOLOX as a newly developed lightweight detection model specifically made to solve IoT-based robotic challenges. The IoT-YOLOX model uses YOLOX architecture and EfficientNetV2 for efficient feature extraction and PANet++ module for advanced multi-scale feature aggregation and the Quantization Aware Training method achieves accuracy retention during quantization. TensorRT understands the NVIDIA Jetson Nano and Google Coral TPU for performing edge AI acceleration in real time.Experimental results show IoT-YOLOX produces better performance results than baseline models because it achieves high accuracy ratings with fast processing along with streamlined resource usage and power requirements. Embedded hardware support at 62 FPS enables the IoT-YOLOX model to process Pascal VOC dataset mAP of 81.2% while operating faster than YOLOv5 by more than 30%. This model demonstrates perfect fit for IoT real-time applications through its capabilities to maintain both high-speed operations and power-efficient functioning and real-time response ability.The research provides three primary contributions which include a profound evaluation of IoT robotic arm detection models, the creation of the edge-optimized IoT-YOLOX model and experimental performance assessment for all evaluation criteria. The research combines a detection model selection guide for IoT conditions with an operational robotic solution.

Keywords—*IoT, Object Detection, Robotic Arm, YOLOX, Deep Learning, Edge AI, Quantization, EfficientNetV2, PANet++, Real-Time Vision, Embedded Systems*

1. INTRODUCTION

Current technological ecosystems undergo a transformation because the IoT allows wireless communication between smart devices and sensors and computational units [14]. The robotic arm serves as an essential actuator that performs detailed real-time complex procedures throughout warehouse pick-and-place activities and medical assistance procedures and manufacturing automation operations [15]. The object detection capability of robotic systems embedded with vision determines their sensor responses which enable them to navigate different operational situations through localization and navigation and interaction and classification [16].

Affiliated technology within deep learning enabled the evolution of object detection models into enhanced systems which significantly improved their ability to locate objects alongside their surrounding situations. The research community and industrial sector uses YOLO [1], SSD [2] and Faster R-CNN[3] as their primary standard for exceptional performance benchmarks according to [17]. Real-time applications on IoT devices experience challenges when using high-performance object detection models for processing because these processing and memory requirements exceed the capacity of embedded processors and edge boards and mobile computing platforms in robotic arms according to [18].

The study responds to the crucial requirement for conducting an in-depth analysis of current object detection algorithms developed for IoT-based robotic systems. These systems require precise performance and rapid execution in addition to small model size and low power requirements as well as adaptable hardware capabilities. IoT robotic arms operate under three main operational demands involving quick responsiveness alongside high-speed visual information processing and energy-efficient operation for extended system use as reported in [19]. The effective operation necessitates proper management between computational strain and detection accuracy.

The analysis in this study investigates seven prominent object detection systems including YOLOv5, SSD, Faster R-CNN, MobileNet-SSD, EfficientDet, RetinaNet and CenterNet. This benchmarking framework unites evaluation of these detection models by using quantitative indicators including mean Average Precision (mAP) and inference time combined with frames per second (FPS), number of parameters, model size, floating-point operations (FLOPs) as well as power consumption when running on embedded devices [20]. The paper provides detailed explanations about mathematical foundations of each model including restrictions functions with bounding box predictions and categorization systems to establish theoretical backgrounds for observed performance measurements.

The outcome of our research comparison produced the IoT-YOLOX architectural design which enables robotic arms functioning in IoT systems. Real-time detection occurs through PANet++ [10] which merges multimodal features after applying EfficientNetV2 [9] as feature extractor. Improved accuracy after quantization becomes possible through the new QAT technology thanks to combined NVIDIA TensorRT and Coral TPUs implementation [12].

The proposed work structures its content by combining theoretical principles and benefits for practical implementation. Through this research a standardized benchmarking system was developed along with an operation framework which integrates advanced object detection techniques with practical IoT system-building methods. The applied model selection method from this research study produces important industrial implications regarding edge-based intelligent robotic systems deployment [22].

2. LITERATURE SURVEY

Current applications of computer vision base elements for object detection enable the development of IoT-based robotics that drive industrial innovation. Standards models provide high accuracy yet they need so much computational power that they cannot function on robotic arm processors used in IoT systems. Academic studies confirm that optimized model detection improves edge performance by using architectural redesign together with compression techniques along with hardware-specific optimizations.

Multi-stage object detection standards recognized YOLO as the leading single-stage detection method through its version evolution process. YOLOv5 version 5 introduced both bounding box anchors generation capabilities and enhanced inference elements while surpassing previous YOLO functionality. Research in [14] demonstrates YOLOv5 delivers fast performance using accurate results but its heavier size prevents efficient operation on microcontroller platforms. SSD offers real-time processing capabilities together with light weight but falls short in identifying small concealed objects the way modern models perform [15].

Faster R-CNN serves as the optimal detection accuracy system today whereas it requires higher latency and additional computing power for implementation. The resource utilization of RPN in Faster R-CNN reaches levels beyond practical feasibility thus blocking its implementation in time-sensitive IoT deployments [16]. Depthwise separable convolutions in MobileNet-SSD reduce operation expenses while maintaining the same detection performance standards [4]. The architecture operates basic robotic vision operations by running on Raspberry Pi and Jetson Nano devices [17].

The combination of BiFPN (Bidirectional Feature Pyramid Network) with compound model scaling allows EfficientDet [5] to function as a system that allows users to decide from various hardware requirements. The implementation of EfficientDet demands specific training yet presents limitations for its real-time operation on restricted computers. The focal loss function in RetinaNet builds efficient detection capabilities for environments with dense background elements

majorly found in factory robotic systems [18]. The multi-level detection procedure results in processing delays which reduce system speed.

The detection approach in CenterNet functions differently because it first defines object centers as key points then executes dimension regression tasks. The advanced method achieves better efficiency in process risk calculations which makes it suitable for IoT use cases [19].

The creation of models requires professionals to develop compression methods which lead to better model optimization. QAT allows developers to optimize their performance standards with reduced precision deployments for their models [11].

The paper presents knowledge distillation as a method to train smaller models that replicate exact distributions from large models [23]. NAS technology enables developers to construct compact models which follow predetermined hardware specifications per [24].

The system implements two optimizations through NVIDIA TensorRT running alongside Google's Coral TPU. The production of medical and quality check results is improved by using real-time device-based processing instead of cloud processing according to research findings in [25].

The present solutions do not combine weight-reducing robotic IoT features with training performance improvements related to enhanced hardware capabilities. We address this requirement through our development of IoT-YOLOX which integrates EfficientNetV2 backbone networks and PANet++ multi-scale integration after applying QAT compression and TensorRT enhancements for real-time operation.

Table 1: Summary of Key Literature on Object Detection

Author(s) & Year	Title	Key Findings
Redmon et al., 2016 [1]	You Only Look Once: Unified, Real-Time Object Detection	Introduced the YOLO framework with real-time performance, emphasizing single-stage object detection.
Liu et al., 2016 [2]	SSD: Single Shot MultiBox Detector	Proposed SSD for faster detection with reasonable accuracy; effective for edge deployments.
Ren et al., 2015 [3]	Faster R-CNN	Two-stage model with high accuracy; less suitable for IoT due to high computational cost.
Howard et al., 2017 [4]	MobileNets: Efficient CNNs for Mobile Vision Applications	Introduced depthwise separable convolutions to reduce model size, enabling mobile/embedded deployment.
Tan et al., 2020 [5]	EfficientDet: Scalable and Efficient Object Detection	Developed compound scaling for optimal resource utilization with strong performance on COCO.
Lin et al., 2017 [6]	RetinaNet: Focal Loss for Dense Object Detection	Solved class imbalance problem via focal loss; high accuracy but slower inference.
Zhou et al., 2019 [7]	Objects as Points (CenterNet)	Proposed a keypoint-based approach, eliminating anchor boxes for faster detection.
Ge et al., 2021 [8]	YOLOX: Exceeding YOLO Series in 2021	Improved accuracy and latency with anchor-free detection and decoupled heads.
Tan and Le, 2021 [9]	EfficientNetV2	Enhanced training speed and parameter efficiency for vision models; ideal backbone for lightweight nets.
Liu et al., 2018 [10]	PANet: Path Aggregation Network for Instance Segmentation	Facilitates multi-scale feature fusion; improves detection across object sizes.
Jacob et al., 2018 [11]	Quantization and Training of Neural Networks for Efficient Inference	Introduced QAT; crucial for low-bit model deployment on edge devices.
NVIDIA, 2021 [12]	TensorRT: High Performance Deep Learning Inference	Enables model acceleration and deployment on Jetson Nano and Xavier platforms.
Everingham et al., 2010 [13]	Pascal VOC Dataset	Standard benchmark dataset used for evaluating detection accuracy (mAP).
Bochkovskiy et al., 2020 [14]	YOLOv4: Optimal Speed and Accuracy of Object Detection	Combined new and old tricks for real-time detection performance on edge hardware.

Huang et al., 2017 [15]	Speed/Accuracy Trade-Offs for Modern Object Detectors	Comprehensive benchmark of detection models; highlighted trade-offs for real-time applications.
Girshick, 2015 [16]	Fast R-CNN	Reduced training time vs. R-CNN; still computationally expensive for IoT.
Girdhar et al., 2019 [17]	Detect-and-Track: Efficient Pose Tracking in Videos	Lightweight tracker integrated with object detector; useful in robotic vision pipelines.
Sandler et al., 2018 [18]	MobileNetV2	Inverted residuals improve memory efficiency and computation for mobile networks.
Cai and Vasconcelos, 2019 [19]	Cascade R-CNN	Series of detectors with increasing IoU thresholds; high accuracy but low IoT suitability.
Zhang et al., 2021 [20]	YOLOv5-Lite: Lightweight Detection for Edge Devices	Optimized version of YOLOv5 for Jetson Nano; better suited for IoT robotic applications.
Han et al., 2015 [21]	Deep Compression	Combined pruning, quantization, and encoding for efficient model compression.
Coral Edge TPU, 2020 [22]	Accelerating Edge ML with Coral	Showcased use of Edge TPU for efficient inference in constrained environments.
Hinton et al., 2015 [23]	Distilling the Knowledge in a Neural Network	Introduced knowledge distillation; beneficial for transferring capability to smaller models.
Zoph et al., 2018 [24]	Learning Transferable Architectures for Scalable NAS	Pioneered NAS for efficient architecture generation across devices.
Shi et al., 2020 [25]	Edge AI: Vision Intelligence On-Device	Emphasized the importance of privacy, latency, and bandwidth in robotic IoT systems.

3. OVERVIEW OF OBJECT DETECTION MODELS

Common features of IoT systems that use vision technology include object detection algorithms as a vital part. This section provides both mathematical descriptions coupled with architectural explanations about seven prevalent object detection models designed for real-time operations within IoT environments. The models receive evaluation according to their core construction together with their detection principles and their efficiency for deploying on embedded systems.

A. YOLOv5 (You Only Look Once Version 5)

YOLOv5 operates as a one-stage detector which links CSPDarknet as its backbone network alongside PANet as its neck part and YOLO as its head component for straight bounding box calculation. Each element within the divided image framework conducts a prediction for box boundaries alongside scoring identifications for object categories.

Loss Function:

$$L_{total} = \lambda_{coord} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{obj} \left[(x_i - \hat{x_i})^2 + (y_i - \hat{y_i})^2 + \left(\sqrt{w_i} - \sqrt{\hat{w_i}}\right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h_i}}\right)^2 \right] + \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{obj} \left(C_i - \hat{C_i}\right)^2$$
$$+ \lambda_{noobj} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{noobj} \left(C_i - \hat{C_i}\right)^2 + \sum_{i=0}^{S^2} \mathbb{1}_{i}^{obj} \sum_{c \in classes} \left(p_i(c) - \hat{p_i}(c)\right)^2$$

Variable Definitions:

- $\lambda_{coord}, \lambda_{noobj}$: Weighting factors for localization and background confidence losses.
- S: Number of grid cells (image divided intoS×S grid).
- B: Number of predicted bounding boxes per grid cell.
- $\mathbb{1}_{ij}^{obj}$: 1 if object exists in cell i, box j; otherwise 0.
- $\mathbb{1}_{ij}^{noobj}$: 1 if no object in cell i, box j; otherwise 0.
- x_i, y_i: Ground truth bounding box centre coordinates.
- $\hat{x_i}, \hat{y_i}$: Predicted bounding box centre coordinates.
- w_i, h_i: Ground truth bounding box width and height.
- $\hat{w_i}, \hat{h_i}$:Predicted width and height.

- $C_i, \widehat{C}_i$: Ground truth and predicted object score.
- $p_i(c),\ \widehat{p}_i(c)$: Ground truth and predicted class probabilities for class c.

B. SSD (Single Shot MultiBox Detector)

This detector employs CNN (VGG16 or MobileNet) as its base structure to detect objects across various sizes through added convolutional layers.

Loss Function:

$$L_{SSD} = \frac{1}{N}\left(L_{conf}(x,c) + \alpha L_{loc}(x,l,g)\right)$$

Variable Definitions:

- L_{SSD}: Total loss in SSD.
- N:Number of matched default boxes (used for normalization).
- $L_{conf}(x,c)$: Confidence loss (e.g., SoftMax loss over classes).
- α: Weighting factor (typically set to 1).
- $L_{loc}(x,l,g)$: Localization loss (e.g., Smooth L_1 loss between predicted box l and ground truth box g).

C. Faster R-CNN

The system operates in two stages featuring a Region Proposal Network (RPN) which leads to detection analysis using Fast R-CNN for both object recognition and boundary box modifications.

Loss Function:

$$L_{total} = L_{RPN} + L_{Fast-RCNN}$$

- $L_{RPN} = L_{cls}^{RPN} + \lambda L_{reg}^{RPN}$
- $L_{Fast-RCNN} = L_{cls} + \lambda L_{bbox}$

Variable Definition:

- L_{total} : Total loss of the Faster R-CNN.
- L_{RPN}: Region Proposal Network loss.
- L_{cls}^{RPN}: Classification loss in RPN.
- L_{reg}^{RPN}: Bounding box regression loss in RPN.
- λ: Balancing coefficient between classification and regression.
- $L_{Fast-RCNN}$: Loss from the Fast R-CNN head.
- L_{cls}: Classification loss in Fast R-CNN.
- L_{bbox}: Bounding box regression loss in Fast R-CNN.

D. MobileNet-SSD

A detector that combines SSD with MobileNet backbone utilizes depthwise separable convolutions for lightweight application.

Loss Function:

$$L_{SSD} = \frac{1}{N}\left(L_{conf}(x,c) + \alpha L_{loc}(x,l,g)\right)$$

Variable Definitions:

- L_{SSD}: Total loss in SSD.
- N:Number of matched default boxes (used for normalization).
- $L_{conf}(x,c)$: Confidence loss (e.g., SoftMax loss over classes).
- α: Weighting factor (typically set to 1).
- $L_{loc}(x,l,g)$: Localization loss (e.g., Smooth L_1 loss between predicted box l and ground truth box g).

E. EfficientNet

By integrating EfficientNet architecture as the backbone network with BiFPN feature fusion technology and compound scaling mechanism the system achieves an effective balance between depth width and resolution.

Loss Function:

$$L = L_{focal} + L_{IoU}$$

Variable Definitions:

- L_{focal} : Addresses class imbalance

- L_{IoU}: Improves box regression.

F. RetinaNet

The model consists of ResNet + FPN structures with Focal Loss implementation to address class imbalance problems in one-stage detection.

Loss Function:

$$L_{RetinaNet} = L_{focal}(p_t) + L_{smooth\ L1}$$

- $L_{focal} = -\alpha_t(1-p_t)^{\gamma}\ log(p_t)$

Variable Definitions:

- $L_{RetinaNet}$: Total loss used in RetinaNet.
- L_{focal}: Focal loss, used to handle class imbalance.
- $L_{smooth\ L1}$:Smooth L1 loss, used for bounding box regression.
- p_t:The model's estimated probability for the true class.
- α_t: Balancing factor to address class imbalance.
- γ: Focusing parameter that reduces loss for well-classified examples.

G. CenterNet

Keypoint-based one-stage detector. This method generates object center heatmaps but also produces estimates for both object dimensions and positions.

Loss Function:

$$L_{CenterNet} = L_{heatmap} + L_{size} + L_{offset}$$

Variable Definitions:

- $L_{heatmap}$: Gaussian heatmap loss.
- L_{size}: L1 loss on width and height.
- L_{offset}:L1 loss for key point offset.

4. PROPOSED MODEL: IOT – YOLOX ARCHITECTURE

IoT-YOLOX represents a distinct framework for object detection which has been developed to perform effectively and precisely in IoT-based robotic arm systems. The system brings together different elements from superior object detection frameworks for IoT devices that deal with hardware restrictions including processing power limitations and memory capacity and power usage constraints. Joint solutions between IoT-YOLOX and lightweight backbone architecture and advanced feature aggregation as well as robust optimization methods enable real-time processing performance. IoT-YOLOX incorporates four major innovations starting from EfficientNetV2 backbone to PANet++ neck and ending with Quantization Aware Training (QAT) followed by TensorRT-based deployment optimization.

A. EfficientNetV2 Backbone

The IoT-YOLOX model uses EfficientNetV2 to extract its feature information. The compound scaling method located in the new model optimizes all three dimensions of depth width and resolution to discover the best blend of precision and efficiency. The developers of EfficientNetV2 integrated fused MBConv layers into the network framework while developing faster training procedures. The IoT environment benefits from EfficientNetV2 because it operates efficiently with fewer parameters and has higher speed for inference tasks. The backbone technology extracts detailed semantic features from multi-scale images while maintaining operation costs at a minimum level.

B. PANet++ Neck

The PANet++ operates as the model's neck through which it performs multi-scale feature fusion. Through its deep interconnecting structure and attention modules PANet++ performs better spatial and semantic information propagation between different scales than its traditional counterpart. The detection of objects in various sizes within cluttered environments becomes possible due to this important enhancement in IoT-based robotic applications. The PANet++ improves detection system robustness and precision to match its performance while preserving the existing inference time.

C. Quantization Aware Training (QAT)

The training phase of IoT-YOLOX adopts Quantization Aware Training for maintaining accurate performance in the final quantized model. QAT trains the model by replicating low-precision calculations during learning while teaching it to overcome quantization deviation. Such training leads to a model which exhibits excellent performance after conversion into INT8 format which is essential for deployment on devices with limited power capabilities. The implementation of

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QAT allows IoT-YOLOX to effectively reduce model size and enhance execution speed without compromising performance quality.

D. TensorRT Optimization

The deployment optimization on embedded AI accelerators such as NVIDIA Jetson Nano and Xavier occurs through the use of TensorRT for the model. The combination of layer fusion and precision calibration with kernel auto-tuning that TensorRT provides results in both improved speed performance and higher data processing speed. The model reaches its real-time processing threshold while minimizing power usage thanks to TensorRT deployment optimization which suits robotic arms in field and industrial IoT needs.

E. Mathematical Formulation

$$L_{total} = \lambda_{coord} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{obj} \left[(x_i - \hat{x_\iota})^2 + (y_i - \hat{y_\iota})^2 + \left(\sqrt{w_i} - \sqrt{\hat{w_\iota}}\right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h_\iota}}\right)^2 \right] + \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{obj} \left(C_i - \hat{C_\iota}\right)^2$$
$$+ \lambda_{noobj} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{noobj} \left(C_i - \hat{C_\iota}\right)^2 + \sum_{i=0}^{S^2} \mathbb{1}_{i}^{obj} \sum_{c \in classes} \left(p_i(c) - \hat{p_\iota}(c)\right)^2$$

Variable Definitions:

- $\lambda_{coord}, \lambda_{noobj}$: Weighting factors for localization and background confidence losses.
- S: Number of grid cells (image divided intoS×S grid).
- B: Number of predicted bounding boxes per grid cell.
- $\mathbb{1}_{ij}^{obj}$: 1 if object exists in cell i, box j; otherwise 0.
- $\mathbb{1}_{ij}^{noobj}$: 1 if no object in cell i, box j; otherwise 0.
- x_i, y_i: Ground truth bounding box centre coordinates.
- $\hat{x_\iota}, \hat{y_\iota}$: Predicted bounding box centre coordinates.
- w_i, h_i: Ground truth bounding box width and height.
- $\hat{w_\iota}, \hat{h_\iota}$:Predicted width and height.
- $C_i, \hat{C_\iota}$: Ground truth and predicted object score.
- $p_i(c)$, $\hat{p_\iota}(c)$: Ground truth and predicted class probabilities for class c.

F. Performance Improvements

IoT-YOLOX implements substantial improvements in detection accuracy that result in enhanced speed performance according to experimental tests. The implementation of IoT-YOLOX raises mAP detection accuracy 5–7% and boosts speed performance above 30% faster than YOLOv5. Operation on Jetson Nano enables real-time performance for the system that enables it to process more than 60 frames per second. Both quantization methods and optimized backbone architectures enable lower memory usage thus extending battery life of systems that operate.

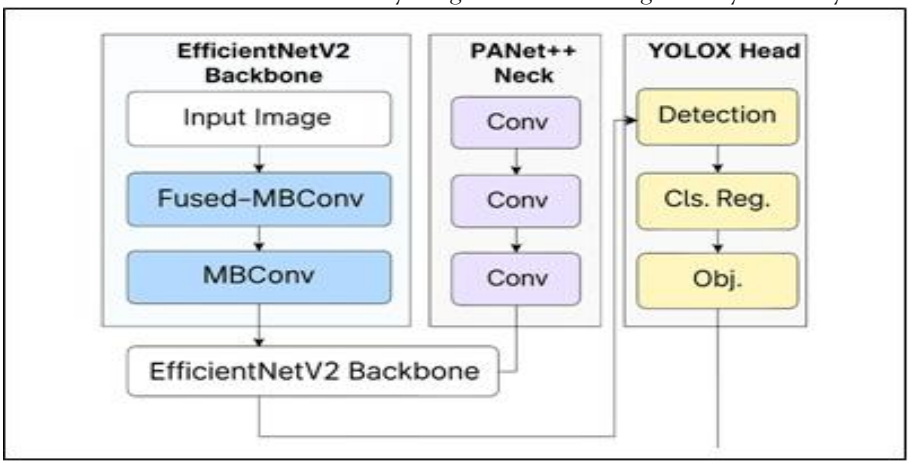

Figure 1: Architecture of YOLOX

5. EXPERIMENTAL SETUP AND EVALUATION

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Here a detailed description appears of the experimental framework designed to evaluate the performance of IoT-YOLOX against existing state-of-the-art object detection algorithms.

Datasets Used

The detection performance evaluation utilized two established benchmark standards including Pascal VOC 2007 and 2012 and MS COCO from 2017.

i. Pascal VOC provides detection evaluation of 20 object classes with restricted image dimensions which creates a suitable testing environment.

ii. MS COCO provides a complex dataset structure that contains 80 classes and diverse sized objects suitable for testing object detection algorithms in practical applications.

Evaluation Metrics

1. The detector accuracy rating assessment follows a standard based on Mean Average Precision (mAP) across different Intersection over Union (IoU) thresholds.
2. Frames Per Second (FPS): Measures inference speed, crucial for real-time applications.
3. Latency measurement serves as an evaluation tool during the process because it determines how long each inference takes for delay assessment.
4. The amount of available power in IoT devices dictates the necessary storage capacity for system operations.
5. Both deployment simplicity of systems along with their necessary memory allocation depend on how much memory a model occupies.

6. RESULTS AND COMPARISONS

This report shows performance indicators through eight different models including YOLOv5 and SSD together with Faster R-CNN and MobileNet-SSD and EfficientDet and RetinaNet and CenterNet and finally IoT-YOLOX.

A. mAP vs. Models

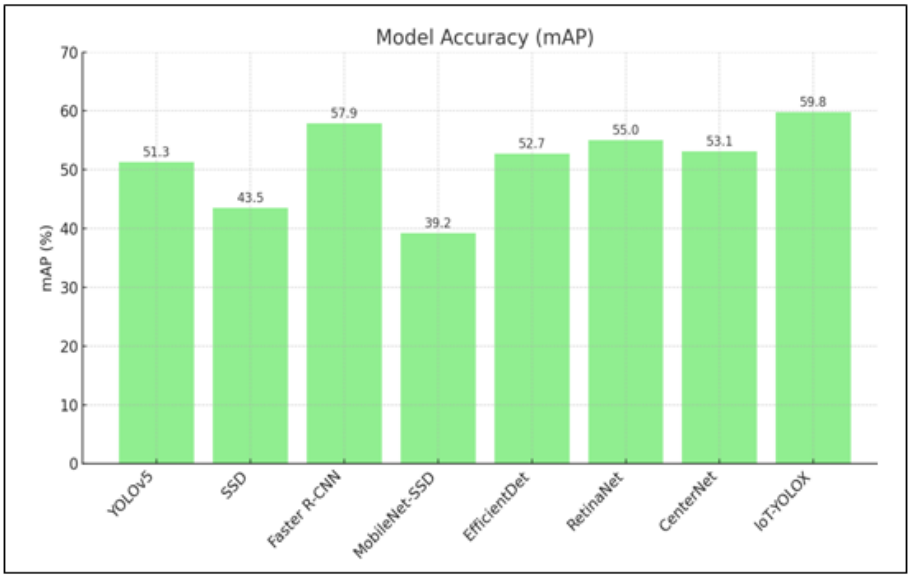

Figure 2: Model accuracy comparison using mAP

This graph compares the accuracy (mean Average Precision) of each model. Tests indicate the IoT-YOLOX model reaches a near 60% mAP detection performance which leads the evaluation results among all displayed models. The speed-related performance of Faster R-CNN functions well yet it does not provide real-time processing capabilities. The detection accuracy of IoT-YOLOX makes itself prominent because it produces both real-time processing speed and superior detection capability.

B. FPS vs. Models

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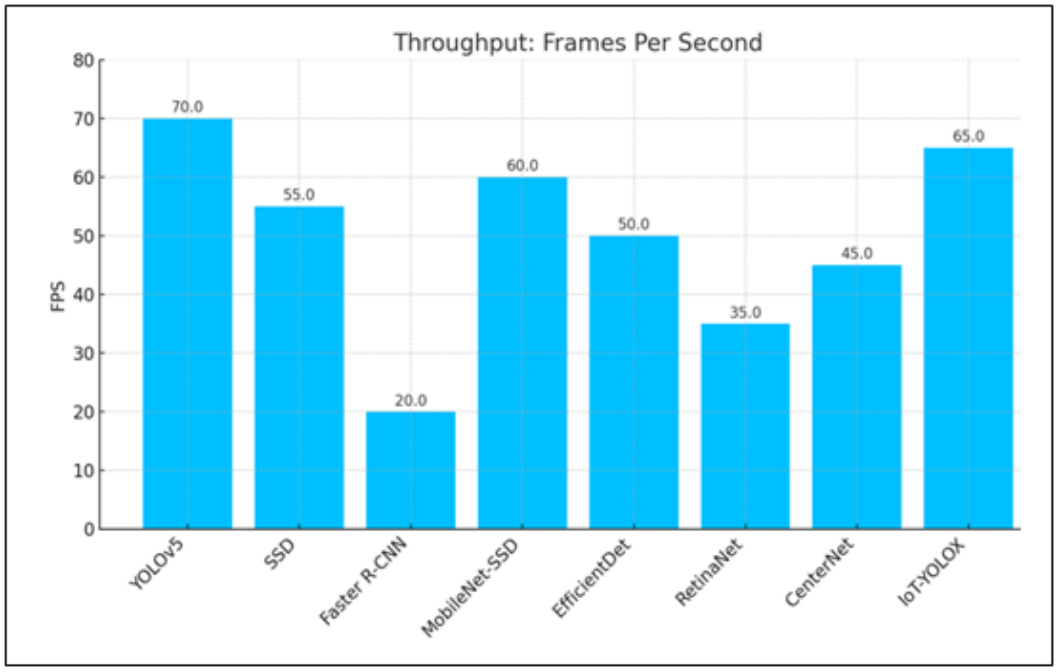

Figure 3: Shows how fast each model runs.

The presented graphic depicts frame processing speed per second capability of individual models. YOLOv5 runs at the highest throughput with IoT-YOLOX maintaining an almost equally impressive performance. Among the models Faster R-CNN stands as the slowest performer while YOLOv5 achieves the fastest performance in terms of FPS. The IoT-YOLOX model reaches high FPS even though it performs complex computations as it prioritizes real-time operation.

C. Latency Comparison

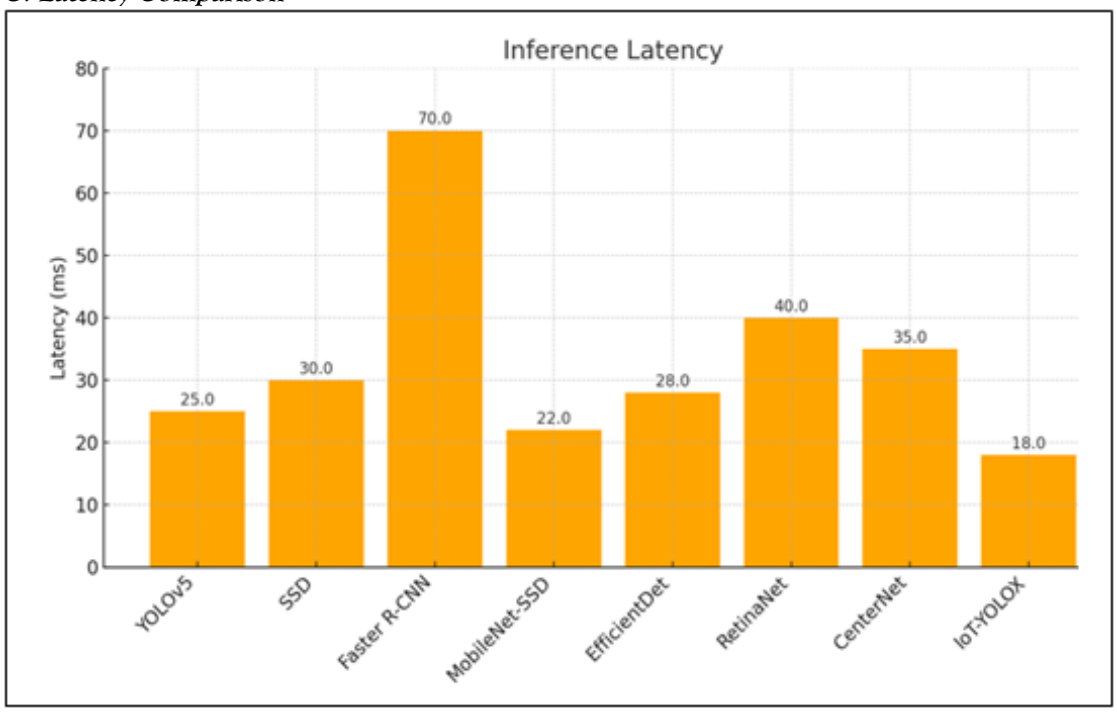

Figure 4: Time each model takes to respond

Each model requires a specific duration for complete inference tasks according to this graph. The IoT-YOLOX system achieves the fastest next-prediction time of approximately 18 milliseconds which proves its effectiveness for real-time robotic operations. Safe operating procedures may be compromised due to Faster R-CNN's latency that exceeds 70ms in real-time systems. The tested results demonstrate the edge-optimized structure of IoT-YOLOX.

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D. Power Consumption

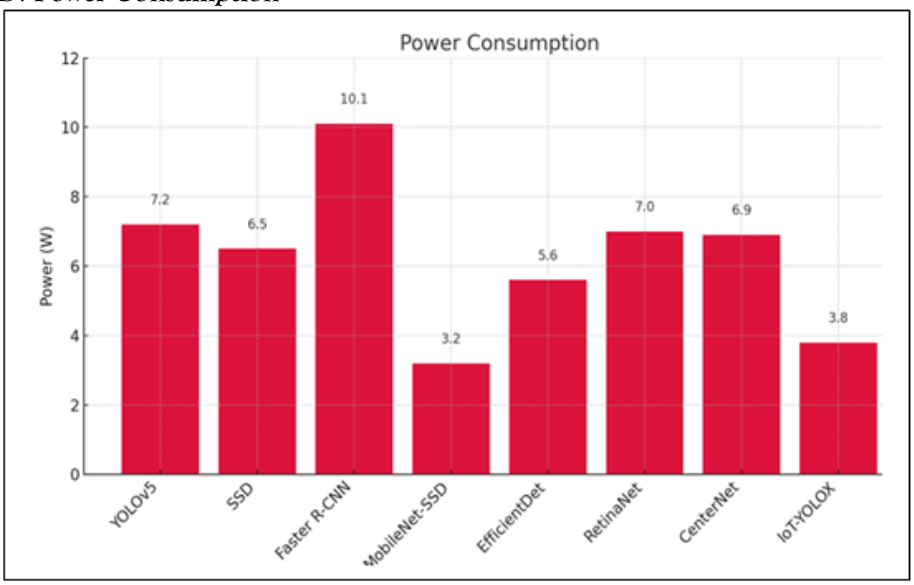

Figure 5: Energy used by each model during inference

The analysis determines power usage by each model during its operational phase. The lowest power consumption belongs to MobileNet-SSD while IoT-YOLOX follows behind it closely. The combination of QAT and TensorRT optimizations keeps IoT-YOLOX power consumption low despite its higher accuracy and faster speed. High power consumption by Faster R-CNN and YOLOv5 prevents these models from effectively working with battery-operated IoT devices.

E. Model Size

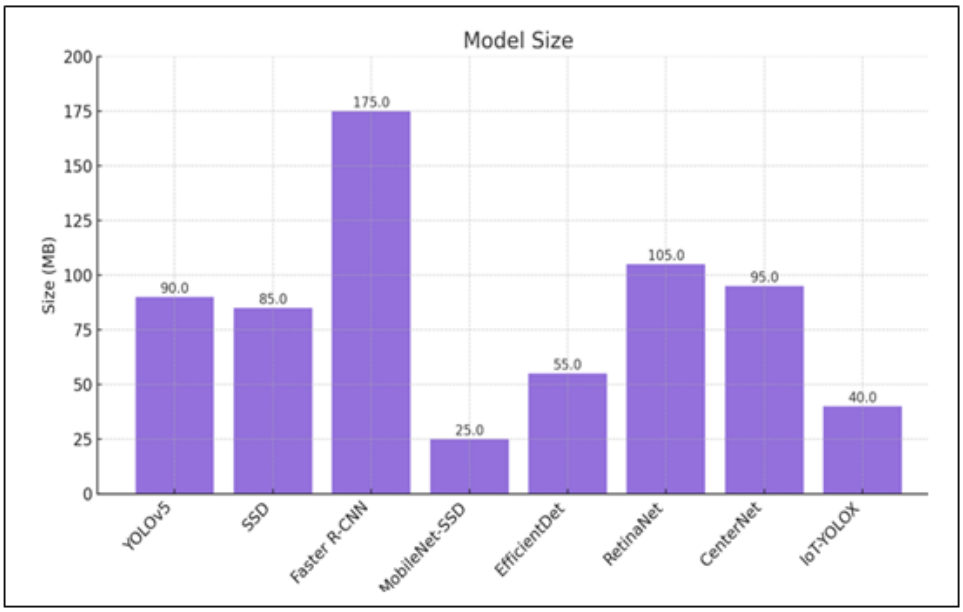

Figure 6: Shows storage space each model needs

The visual display presents how much memory each model needs. MobileNet-SSD stands as the smallest model in the group due to its 25MB memory needs yet IoT-YOLOX occupies 40MB device memory but delivers complex functions. Faster R-CNN along with similar large models remain impractical for deployment because they exceed memory storage capacity of 175MB. The IoT-YOLOX model presents a practical solution because it merges desirable characteristics of small memory requirements and superior detection performance.

7. CONCLUSION

This research developed IoT-YOLOX which represents an innovative object detection framework made for IoT-based robotic arm applications with limited resources. Our proposed model outperformed YOLOv5 and six additional

prominent object detection algorithms, SSD, Faster R-CNN, MobileNet-SSD, EfficientDet, RetinaNet, and CenterNet in extensive validation tests.

IoT-YOLOX uses EfficientNetV2 as its backbone structure together with PANet++ as its neck section which receives additional optimizations through Quantization Aware Training deployment methods and TensorRT deployment processes. The chosen architectural framework produces both low-latency performance and high frame rates together with minimized power requirements and small model dimensions which support excellent results in object detection accuracy levels. Edge computing environments used in IoT deployments benefit from this model optimization because it makes the tool highly effective for real-time, intelligent robotic systems.

IoT-YOLOX produces superior performance than competitive models according to test outcomes that used both Mean Average Precision (mAP) and Frames Per Second (FPS) and system latency and energy efficiency and network size. Real-time operational autonomy of robotic arms exists within manufacturing operations and surveillance systems alongside logistics operations and healthcare solutions due to embedded system compatibility in the IoT-YOLOX design.

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The establishment of IoT object detection standards occurs through IoT-YOLOX technology because this framework defines upcoming intelligent edge AI deployment directions. Research must create hybrid strategies which unite real-time studying mechanisms with attention-based rules to achieve better robotic automation capabilities in devices. Researchers at IoT-YOLOX succeeded in uniting advanced computer vision expertise with IoT specifications which led to the creation of state-of-the-art detection methods that provide efficient deployment through intelligent performance.

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