

¹Punith Kumar,²Champa H N

Enhancing Pollinator Protection Using Real-Time Visual Recognition



Abstract: - In the context of accelerating climate change and its detrimental impact on global food systems, the integration of advanced technologies for monitoring pollinator populations has become critical for ensuring environmental sustainability and food security. The preservation of pollinators is essential for human survival. This study investigates the application of Computer Vision and Object Detection techniques to automatically analyze bee activity through image data. A new dataset comprising 6,993 bee-containing images was curated from video footage and manually labeled using bounding boxes. The dataset was divided into training (5,203), validation (902), and testing (828) subsets. Evaluation of various fine-tuned YOLO models based on the COCO framework revealed that YOLO v5 m delivers the highest recognition accuracy. Nevertheless, YOLO v5 s emerged as the most efficient for real-time detection tasks, achieving an average inference time of 5.7 milliseconds per frame, albeit with a modest reduction in detection performance. The final model was embedded within an explainable AI system that generates time stamped visual summaries, allowing easy interpretation by non-technical users, including key stakeholders in the apiculture sector, to support sustainable practices in pollinator management.

Keywords: YOLO, global, apiculture, pollinator, accuracy

I. INTRODUCTION

The pollination services provided by bees play a crucial role in the fruit and seed production of most plant species, directly impacting agricultural productivity and economic outcomes [1]. Pollination is essential to global agriculture, as approximately 75% of flowering plant species and 35% of food crops rely on it for successful reproduction [2]. According to the Food and Agriculture Organization (FAO) of the United Nations, out of the slightly over 100 crop species that account for 90% of the global food supply across 146 countries, 71 rely on bee pollination primarily from wild bees while others depend on pollination by insects such as thrips, wasps, flies, beetles, and moths [3]. Numerous studies have highlighted that bees and other pollinators are facing significant threats, with an estimated 40% of invertebrate pollinator species at risk of decline [4]. Bee colonies encounter numerous challenges affecting their development, reproduction, and long-term viability, including climate change, pesticide exposure, land use changes, and management practices. Recognizing these factors is crucial to ensuring effective pollination [5]. Honey bee populations are facing growing health challenges due to a combination of pervasive parasitic infections, emerging threats, and the extensive effects of globalization and climate change. These combined pressures have led to a noticeable increase in colony losses worldwide [6]. Precision Beekeeping, aims to assist beekeepers by enabling remote monitoring of hive conditions and identifying diverse behavioral patterns, including signs of irregular activity [7]. Fuzzy logic decision-making systems have been utilized to assess hive health by analyzing temperature data collected from both the interior of the hive and its external environment [8]. Identifying the presence of diseases like Varroa, which commonly occur under specific temperature and humidity conditions, helps beekeepers prevent hive collapse [9]. Swarming events in beehives have been detected using various machine learning methods, including k-Nearest Neighbors (k-NN), Support Vector Machines (SVM), and Convolutional Neural Networks, particularly models based on the U-Net architecture [10]. Data augmentation is a widely used strategy in deep learning aimed at improving model performance by creating additional training samples from the original dataset through various transformation methods [11]. Distance-IOU (DIOU) loss integrates the normalized distance between the predicted and ground truth boxes, resulting in significantly faster convergence during training compared to traditional IOU and GIoU loss functions [12]. Experiments were conducted on real-world visual grounding datasets to validate the effectiveness of the DIOU loss function [13]. Beyond beekeeping applications, digital technologies are increasingly being explored across broader agricultural settings. Digital technologies including autonomous robotic systems, the Internet of Things, and machine learning have been extensively investigated, with a majority of research (69%) focusing on open-air farms compared to indoor farming systems (31%) [14]. In the current digital age, the volume of publicly available video content has grown exponentially. Processing and interpreting this vast amount of data demands robust and efficient content-based video analysis techniques. One such approach involves identifying abrupt shot transitions and selecting

^{1,2}Department of Computer Science and Engineering, University Visvesvaraya College of Engineering, Bengaluru, India.

* Corresponding author's Email: 1punithkumar87@gmail.com, 2champahn@yahoo.co.in

keyframes that best represent each video segment [15]. Integrating CNNs with recurrent neural networks (RNNs) creates a robust framework for video classification, enabling efficient and simultaneous processing of spatial and temporal information [16].

The rest of the manuscript is organized as follows. Section 2 describes the related work on existing methods. Section 3 contains the predictive methods used and section 4 includes the results and discussion. Section 5 presents the conclusion drawn from the study.

II. RELATED WORK

Precision beekeeping leverages sensor technologies and artificial intelligence to monitor internal hive conditions, support early disease detection, and enhance the overall management and optimization of beehive environments [17]. The global dependence on animal pollinators for crop production intended for human consumption has not been comprehensively assessed, and earlier estimates at national or continental levels have rarely been based on primary data [18]. Pollination enhances both the uniformity and quality of seeds. In large scale monoculture farming, such as sunflower cultivation, it becomes essential to introduce a substantial number of bees at the onset of flowering. This need is effectively met through mobile beekeeping a flexible and adaptive method that enables beekeepers to relocate hives as needed, thereby supporting better pollination and boosting honey yields [19]. The harmful effects of pesticides especially insecticides on bees and other pollinators are well-established. Insecticides can cause direct mortality among pollinators, while herbicides indirectly impact them by diminishing the variety and availability of floral resources essential for their survival and reproduction [20]. Bees serve as key pollinators for a wide range of crops, with the European dark bee (*Apis mellifera mellifera* L.) being commonly employed for pollination services. However, the extensive use of pesticides in modern agriculture poses a significant threat to the crucial interaction between plants and their bee pollinators. Notably, there is a shortage of comprehensive data on lethal exposure times, insecticide concentrations, and observable poisoning symptoms particularly for commercial insecticide formulations widely used in pest control [21].

A range of environmental monitoring (EM) techniques is explored, focusing on variations in hardware implementation and algorithmic design. The overview emphasizes current state-of-the-art practices, particularly highlighting energy-efficient and low-cost EM system solutions [22]. The thematic evaluation of pollinators, pollination, and food production conducted by the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) seeks to examine animal-mediated pollination as a key regulatory ecosystem service. This service is recognized for its critical role in sustaining food production and contributing to human well-being and the benefits derived from nature [23]. Analysis of acoustic data gathered via smart sensor networks enables the prediction of internal hive conditions and detection of queen bee presence [24]. BeeSense employs Internet of Things (IoT) devices, such as temperature and humidity sensors, to continuously track and assess the internal environment of beehives [25]. YOLO has emerged as a key real-time object detection framework widely used in robotics, autonomous vehicles, and video surveillance. This work provides an in-depth review of YOLO's development, highlighting the advancements and features introduced across its versions, from the initial YOLO model to YOLOv8, YOLO-NAS, and transformer-enhanced YOLO architectures [26]. Integrating advanced information technologies with decision support systems facilitates efficient beehive management, enhancing the survival rates of bee colonies through automated and informed decision-making processes [27]. Object detection methods form a fundamental part of artificial intelligence. This study provides a concise overview of the You Only Look Once (YOLO) algorithm along with its later advanced versions. The analysis highlights key observations and valuable insights, outlining both the similarities and differences among various YOLO iterations as well as between YOLO and traditional CNNs [28]. A real-time imaging system is presented for monitoring honey bee activity by counting bees entering and exiting the hive. Continuous images are captured at the hive entrance, and honey bees are segmented and detected using a background subtraction technique. Tracking individual bees is achieved by integrating a Kalman Filter with the Hungarian algorithm [29]. IoT sensors monitor temperature and humidity to maintain optimal conditions for bees, while continuous tracking of beehive weight helps assess hive health and productivity [30]. Object detection and tracking play a crucial role in computer vision and visual surveillance by enabling the identification, recognition, and continuous monitoring of objects within images or video sequences. These processes form the backbone of surveillance systems, supporting automatic video annotation, event recognition, and the detection of unusual activities [31]. Similar to other biofuel crops, data on how insect

pollinators and landscape context influence the productivity and sustainability of *Jatropha curcas* remain limited. This study examined the effects of pollinator exclusion, self-pollination, cross-pollination, and individual visits by the stingless bee *Friesia Melitta nigra* and the honey bee *Apis mellifera* on fruit set, as well as the weight of fruit and seed in *J. curcas* [32]. HiveLink employs advanced sensors to continuously monitor internal hive conditions, including humidity, temperature, and weight [33]. The BHiveSense architecture enables monitoring of bee colonies using a low-cost sensing prototype, facilitating the prediction of internal beehive conditions [34].

III. METHODS

The data collection and preprocessing, model training and data augmentation approaches and web-based detection interface is explained in below section.

3.1 Dataset Collection and Preprocessing

An image dataset was compiled to support automated bee detection, comprising approximately 6,993 labeled images with around 12,655 total bee annotations. Each image features an average of 1.8 bees, with most containing a single bee. The dataset includes a few images with high bee density, with up to 12 bees detected in a single frame. During the annotation process, images with quality issues such as heavy blur or obstructions were excluded. Original image resolutions ranged between 0.2 MP and 2.5 MP, with a median resolution close to 1280×720 pixels. To align with the YOLO input requirements, all images were resized to 416×416 pixels, and the associated bounding box coordinates were scaled using OpenCV to maintain proportional accuracy. The dataset contains various bee species, primarily including *Apis mellifera* species. Differences in camera angle and bee posture resulted in a variety of annotation sizes and aspect ratios. Figure 1 shows the sample annotated images for random dataset. Figure 2 shows the distribution of the number of bees per image within the dataset. The dataset is made publicly accessible for research purposes and is accessible in <https://www.kaggle.com/datasets/birdy654/bee-detection-in-the-wild>.



Fig. 1. Sample annotated images (red bounding boxes) and corresponding preprocessed versions selected randomly from the dataset.

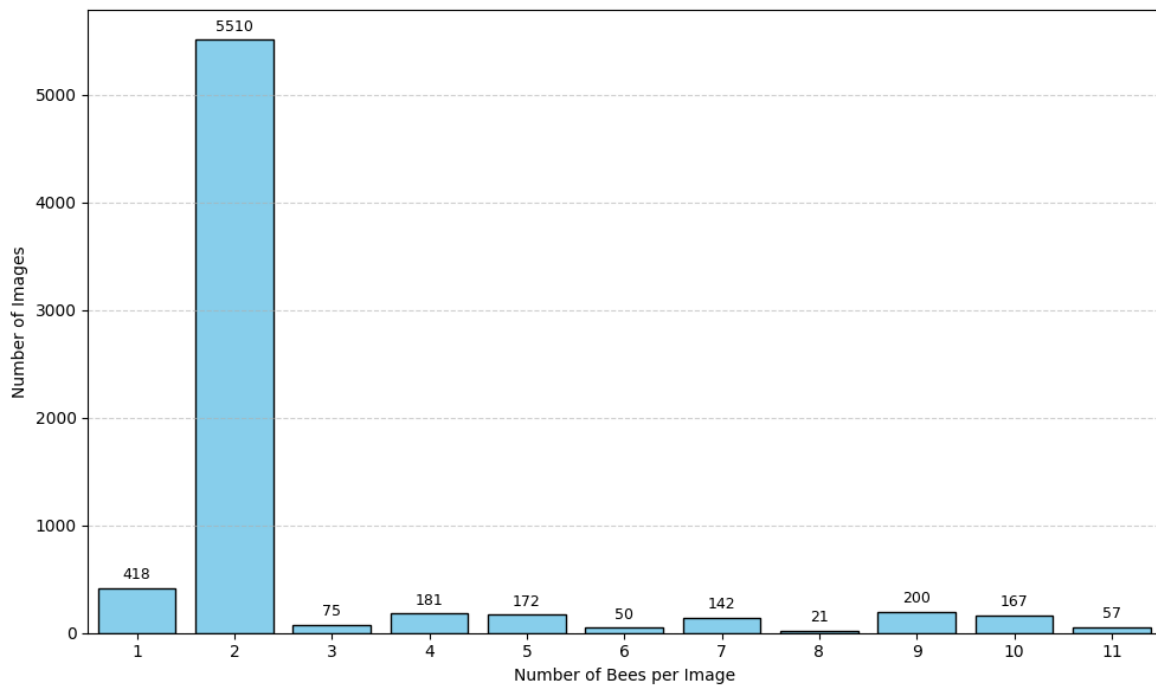


Fig. 2. Distribution of the number of bees per image in the dataset, showing frequency counts with one dominant category.

3.2 Model Training and Data Augmentation

State of the art object detection algorithms such as YOLOv5, YOLOv5m, YOLOv5s, and YOLOv8m were evaluated using the compiled dataset. Instead of customizing data augmentation pipelines, the models were trained using default augmentation strategies. A preliminary test phase was conducted on 828 randomly selected images, training YOLOv5 models with and without augmentation for 30 training epochs. This step aimed to assess whether augmentation significantly enhanced model performance. Augmentation was applied in real time during training, keeping the stored dataset unchanged. Subsequently, full model training was executed over 100 epochs, and performance was evaluated using metrics such as precision, recall, mean Average Precision at IoU 0.5 (mAP@0.5), mAP@[0.5:0.95], training time, and inference speed. These evaluations ensured the model's suitability for real-time use with limited computational resources.

3.3 Web-Based Detection Interface

A prototype interface was designed for stakeholder use and is shown in Figure 3, enabling real-time bee activity monitoring through video/image uploads. The application extracts keyframes at half the original frame rate (FPS/2) and processes them using the trained object detection model. Each frame is scanned for bee presence, and detection events are timestamped. The system logs the number of bees per frame into a structured CSV file for easy visualization and further analysis. This accessible design bridges field-collected video data with automated inference, providing practical tools for researchers and beekeepers to monitor hive activity without requiring deep technical expertise.

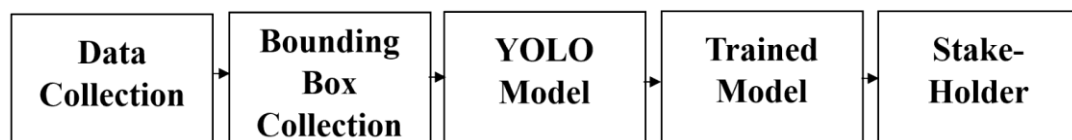


Fig. 3. Prototype interface for stakeholders

IV. RESULTS AND DISCUSSION

This section details the outcomes of model training and validation, followed by the evaluation of object detection performance on unseen test data. Additionally, a sample user interface designed for stakeholder accessibility is showcased, accompanied by a comprehensive discussion of the experimental findings.

4.1 Exploratory study

To evaluate the effectiveness of various YOLO architectures, key performance metrics such as precision, recall, mean Average Precision (mAP), training duration, and inference speed were analyzed. The figure 4 illustrates the training and validation loss curves for two key metrics bounding box loss and objectiveness loss across 30 training epochs for both augmented and non-augmented datasets. Subplots (a) and (b) show the evolution of bounding box loss during training and validation respectively. It is observed that both models exhibit decreasing trends, but the augmented dataset consistently yields slightly higher losses in training, while producing comparable or marginally better performance during validation, especially in later epochs. Subplots (c) and (d) present the objectiveness loss trends for training and validation. The non-augmented model starts with a slightly higher loss but eventually converges more sharply during training, whereas the augmented model demonstrates better generalization on validation data with consistently lower loss values. These results suggest that while data augmentation may slightly hinder convergence speed during training, it offers improved generalization and robustness on unseen validation data.

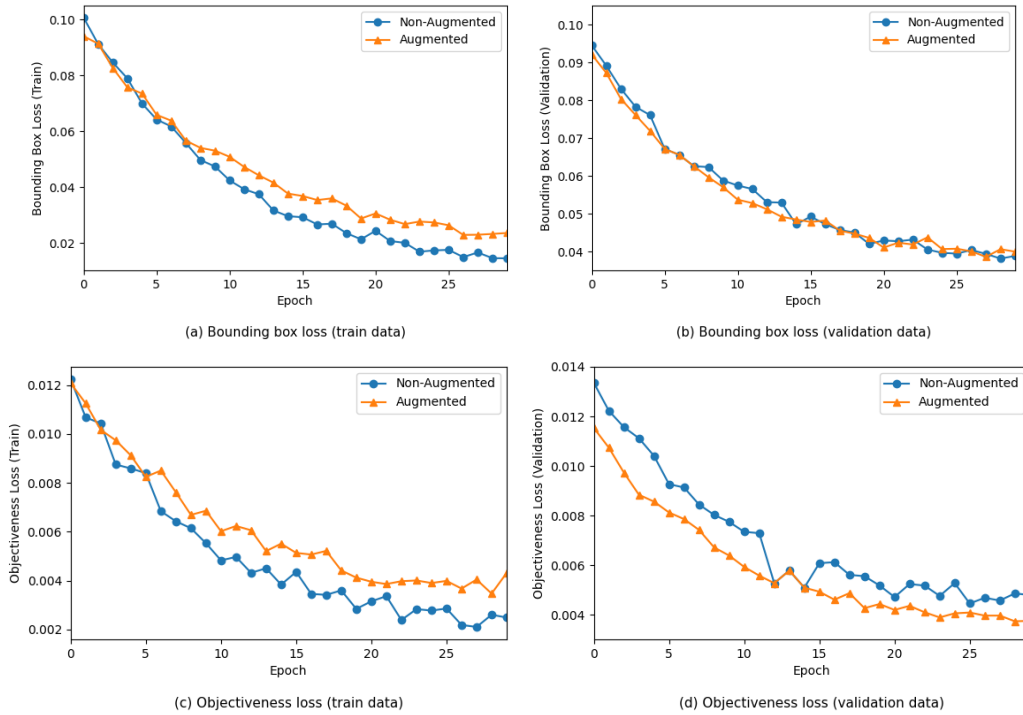


Fig. 4. Metric comparison of bounding box loss (Figs.(a) and (b)) and objectiveness loss (Figs. (c) and (d)) for a non-augmented and augmented subset of training and validation data measured over 30 epochs.

Note: y-axis scales are not comparable.

Figure 5 presents a comparative analysis of training and validation performance metrics precision, recall, mAP@0.5, and mAP@0.5:0.95 between non-augmented and augmented datasets over 30 epochs. In all subplots (a–d), the orange line (Augmented) consistently outperforms the blue line (non-Augmented), indicating that data augmentation positively impacts model performance. Specifically, precision and recall (subplots a and b) both show a steady upward trend with augmentation yielding better scores throughout. Similarly, in subplot (c), mAP@0.5 improves more rapidly and achieves higher values with augmentation. Although mAP@0.5:0.95 (subplot d) exhibits greater variability, the augmented data still shows a clear advantage, especially in the later epochs. It is

important to note that the y-axis scale in subplot (d) is significantly different from the other three, which affects visual comparison. Overall, the graph highlights that data augmentation enhances model generalization and detection performance across key evaluation metrics.

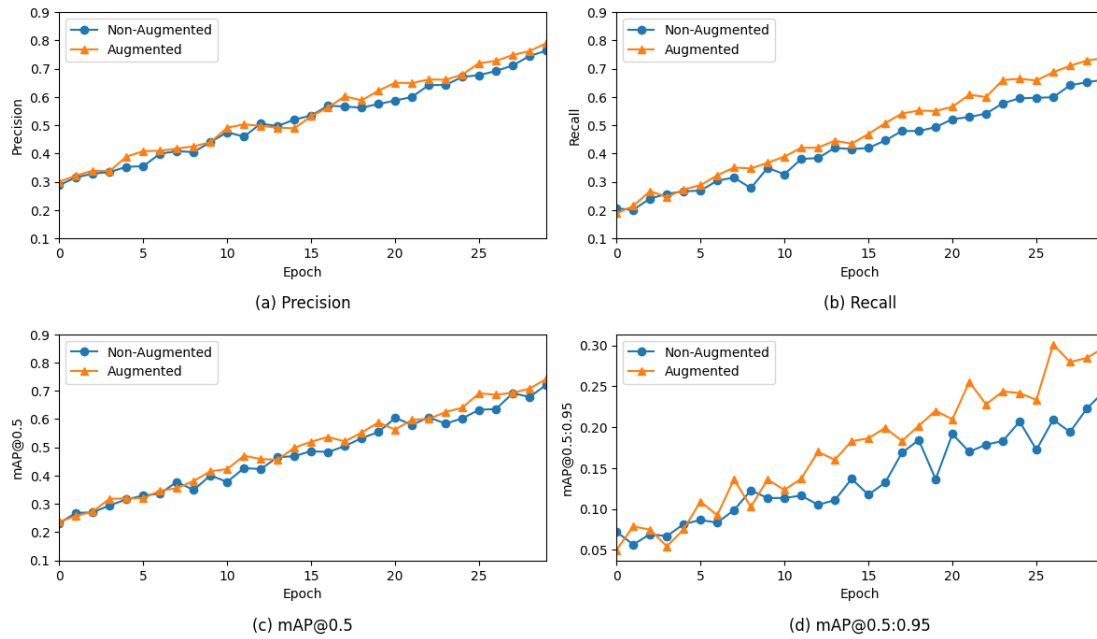


Fig. 5. Performance Metric Comparison (a)Precision, (b)Recall, (c)mAP@0.5 and (d)mAP@0.5:0.95 between non-augmented and augmented subsets of training and validation data over 30 epochs.

4.2 Training results

Table 1 presents a comparative summary of performance metrics for various YOLO model configurations, specifically Base YOLOv5, YOLOv5m, YOLOv5s, and YOLOv8, YOLOv8m, YOLOv8l. Among the models, YOLOv8l exhibits the highest overall performance, achieving the best precision (82.6), recall (81.6), and mAP scores 85.0 at IoU threshold 0.5 and 40.1 at a range of 0.5 to 0.95. YOLOv5s follows closely with strong precision (81.5) and efficient inference speed (6.2 ms), making it suitable for real-time applications. YOLOv5m offers a balanced trade-off with decent precision (81.2), recall (80.7), and mAP metrics while maintaining a moderate inference time. Notably, the training time required increases progressively from YOLOv5s (123 min) to YOLOv8 (214 min), highlighting the computational demand of more advanced models. The base YOLOv5 model lags behind in most metrics, particularly in recall (72.2) and mAP@0.5:0.95 (30.5), emphasizing the performance improvements brought by the newer variants. Overall, YOLOv8l demonstrates superior accuracy and efficiency in object detection tasks, albeit at the cost of higher training requirements.

Table 1: Performance Summary of YOLOv5 and YOLOv8 Model Variants

Metric	Base YOLOv5	YOLOv5m	YOLOv5s	YOLOv8	YOLOv8m	YOLOv8l
Precision	80.1	81.2	81.5	81.8	82.2	82.6
Recall	72.2	80.7	78.7	80.4	81.1	81.6
mAP@0.5	75.8	81.4	81.0	83.3	85.3	85.0
mAP@0.5:0.95	30.5	35.4	34.3	37.8	41.2	40.1
Training Time (min)	120	164	123	214	252	219
Inference Speed (ms)	6.8	7.7	6.2	4.2	5.3	4.0

4.3 Testing results

A comparison of various YOLO model variants Base YOLOv5, YOLOv5m, YOLOv5s, and YOLOv8m based on their performance metrics and inference speed on test data are represented in Table 2. Among the models, YOLOv5m achieves the highest overall detection performance, with a precision of 83.0%, recall of 81.3%, and the highest mAP@0.5 and mAP@0.5:0.95 values at 85.3% and 42.0%, respectively. YOLOv5s follows closely in performance but with a significantly faster inference speed (5.2 ms), making it a balanced choice for both accuracy and efficiency. In contrast, YOLOv8m, despite offering competitive precision and recall, exhibits the slowest inference speed at 12.3 ms. The Base YOLOv5 model shows the lowest performance across most metrics but offers the fastest processing time at 4.9 ms. These results suggest that while more advanced models yield better accuracy, they generally require higher computational resources. Similarly, Table 3 provides a breakdown of the average processing time for different stages pre-processing, inference, and non-maximum suppression (NMS) across various YOLO models. The Base YOLOv5 model exhibits the lowest total processing time at 4.8 ms, with inference contributing the most (3.5 ms). YOLOv5s has a slightly higher total time of 5.2 ms due to increased NMS duration, while still maintaining fast inference. YOLOv5m, though more accurate (as seen in the previous table), requires significantly more inference time (6.8 ms), raising the total to 8.3 ms. YOLOv8m has the highest total time of 12.5 ms, largely due to longer pre-processing (0.8 ms) and inference (10.2 ms) stages. This detailed view highlights the trade-offs between model complexity and real-time performance, making it easier to select a model based on system constraints and speed requirements.

Table 2: Comparative Evaluation of YOLO Model Variants on Object Detection Performance and Inference Speed

Metric	Precision	Recall	mAP@0.5	mAP@0.5:0.95	Inference Speed (ms)
Base YOLOv5	81.6	76.7	81.3	38.1	4.9
YOLOv5m	83.0	81.3	85.3	42.0	8.3
YOLOv5s	82.8	80.1	84.5	41.2	5.2
YOLOv8m	82.0	80.5	83.1	37.5	12.3

Table 3: Detailed Breakdown of Average Processing Time Components for YOLO Models on Test Data

Metric	Average processing time (ms)			
	Pre-process	Inference	NMS	Total
Base YOLOv5	0.1	3.5	1.2	4.8
YOLOv5m	0.1	6.8	1.4	8.3
YOLOv5s	0.1	3.6	1.5	5.2
YOLOv8m	0.8	10.2	1.5	12.5

V. CONCLUSION AND FUTURE WORK

This study systematically evaluated the performance of multiple YOLO object detection models namely Base YOLOv5, YOLOv5s, YOLOv5m, and YOLOv8, YOLOv8m, YOLOv8l across both augmented and non-augmented datasets. The findings clearly demonstrate that data augmentation plays a crucial role in enhancing model generalization, as reflected by improved validation metrics such as precision, recall, and mAP scores. Among the tested architectures, YOLOv8l emerged as the most accurate, though it required significantly higher training and inference times. Conversely, YOLOv5s offered a competitive balance between speed and accuracy, making it an attractive option for real-time applications with limited computational resources. Analysis of training curves further revealed that augmentation may slightly slow convergence during training but results in superior performance on unseen data. The detailed runtime breakdown also provided critical insights into the computational costs associated with different model stages, offering practical guidance for deployment scenarios.

Future work will focus on expanding the scope of this research to more complex and diverse datasets, potentially involving real-world surveillance or agricultural environments. Incorporating lightweight models such as YOLO-Nano or employing model pruning and quantization techniques may offer further reductions in inference latency, making advanced object detection feasible on edge devices. Additionally, integrating attention mechanisms or

transformer-based enhancements into the YOLO architecture could further improve detection accuracy, particularly for small or occluded objects. To support end-user interaction, future iterations will also involve refining the graphical user interface to allow real-time model inference, customization of detection thresholds, and visualization of detection confidence—all aimed at making object detection systems more accessible and operational in dynamic environments.

REFERENCES

- [1] Rollin O., and Garibaldi L.A. (2019). Impacts of honeybee density on crop yield: A meta-analysis. *Journal of Applied Ecology*, 56, 1152-1163.
- [2] Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES). 2019.
- [3] Kluser, S., Peduzzi, P. (2007). Global pollinator decline: a literature review. Geneva: UNEP/GRID.
- [4] Food and Agriculture Organization of the United Nations. (2018). The importance of bees and other pollinators for food and agriculture.
- [5] Khalifa A., Elshafiey, Shetaia, El-Wahed A., Algethami, Musharraf, AlAjmi, Zhao C., Masry H., Abdel-Daim. (2021). Overview of bee pollination and its economic value for crop production. *Insects*.
- [6] Patcharin P., Chainarong S., Korrawat A., Sasiprapa K., Thunyarat C., Tial C., Jeffery S., Panuwan C., Veeranan C. & Terd D. (2023). Preliminary Survey of Pathogens in the Asian Honey Bee (*Apis cerana*) in Thailand. *Life*. <https://doi.org/10.3390/life13020438>.
- [7] Zacepins A., Armands K., Egils S., Marta L. & Jurijs M. (2016). Remote detection of the swarming of honey bee colonies by single-point temperature monitoring. *Biosystems Engineering*.
- [8] Kviesis, A. komasilvos, V. Komasilova and Zacepins A. (2020). Application of fuzzy logic for honey bee colony state detection based on temperature data. *Biosystems Engineering*.
- [9] Nazzi F. and Le Conte Y. (2016). Ecology of varroa destructor, the major ectoparasite of the western honey bee, *Apis mellifera*. *Annual Review of Entomology*.
- [10] Kiromitis I. Dimitrios, Christos V. Bellos, Konstantinos A. Stefanou, Georgios S. Stergios, Ioannis Andrikos, Thomas Katsantas and Sotirios Kontogiannis. (2022). "Performance Evaluation of classification Algorithms to Detect Bee Swarming Events Using Sound". *Signals*. <https://doi.org/10.3390/signals3040048>.
- [11] Bhuse, P., Singh, B., Raut, P. (2022). Effect of data augmentation on the accuracy of convolutional neural networks. In: *Information and Communication Technology for Competitive Strategies (ICTCS 2020) ICT: Applications and Social Interfaces*. Springer, pp. 337–348.
- [12] Zheng Z., Wang P., Liu W., Li J., Ye R., Ren D. (2020). Distance-IoU loss: Faster and better learning for bounding box regression. In: *Proceedings of the AAAI Conference on Artificial Intelligence*.
- [13] Xiang C., Yu Z., Zhu S., Yu J., Yang X. (2019). End-to-end visual grounding via region proposal networks and bilinear pooling. *IET Computer Vision*.
- [14] Abbasi, R., Martinez, P., Ahmad, R. (2022). The digitization of agricultural industry asystematic literature review on agriculture 4.0. *Smart Agriculture Technology*.
- [15] Rashmi, B., Nagendraswamy, H. (2018). Effective video shot boundary detection and key frame selection using soft computing techniques. *International Journal Computer Vision and Image Processing (IJCVIP)*.
- [16] Savran Kızıltepe R., Gan J.Q., Escobar J.J. (2023). A novel keyframe extraction method for video classification using deep neural networks. *Neural Computing and Applications*.
- [17] Anupam Bharadwaj, Arun Babu, C.G. Raghavendra, Gaurav Datta, Vishnu Bhat, Santhosh Kumar (2024). Digital Apiaries: IoT solutions for Modern Beekeepers.
- [18] Klein A.M., Vaissiere B.E., Cane J.H., Steffan-Dewenter I., Cunningham S.A., Kremen C., Tscharntke T. (2007). Importance of pollinators in changing landscapes for world crops. *Proceedings of the Royal Society B. Biological Sciences*.
- [19] Komlatskiy G., Makarova T. (2023). Pollination by bees in industrial crop production. In: *BIO Web of Conferences*, vol. 66, EDP Sciences.
- [20] Sanchez-Bayo F., Goulson D., Pennacchio F., Nazzi F., Goka K., Desneux N. (2016). Are bee diseases linked to pesticides?-A brief review. *Environment International*. <https://doi.org/10.1016/j.envint.2016.01.009>.
- [21] Pashte V.V., Patil C.S. (2018). Toxicity and poisoning symptoms of selected insecticides to Honey Bees (*Apis mellifera* L.). *Archives of Biological Sciences*.

- [22] Kumar A., Kim H., Hancke G.P. (2012). Environmental monitoring systems: A review. *IEEE Sensors Journal*.
- [23] Potts S.G., Ngo H.T., Biesmeijer J.C., Breeze T.D., Dicks L.V., Garibaldi L.A., Hill R., Settele J., Vanbergen A. (2016). The Assessment Report of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services on Pollinators, Pollination and Food Production. Secretariat of the Intergovernmental Science Policy Platform on Biodiversity.
- [24] Michaela Sakova, Patrik Jurik, Pavol Galajda, M. Sokol. (2024). Bee hive acoustic monitoring and processing using convolutional neural network and machine learning.
- [25] Karan I, Getzi Jeba Leelipushpam Paulraj, Immanuel Johnraja Jebadurai, Jerry Allwin J, Sharan D, Sharon Jemimah Peace C. (2024). BeeSense - A Smart Beehive Monitoring System for sustainable Apiculture.
- [26] Terven J., Cordova-Esparza D.M., Romero-Gonzalez J.A. (2023). A comprehensive review of Yolo architectures in computer vision: From Yolo v1 to Yolo v8 and Yolo-NAS. *Machine Learning and Knowledge Extraction*.
- [27] Vitalijs Komasilovs, Rob Millis, Armands Kviesis, Francesco Mandada, Aleksejs Zacepins. (2024). Architecture of a decentralized decision support system for futuristic beehives.
- [28] Jiang P., Ergu D., Liu F., Ying C., Bo Ma. (2022). A review of Yolo algorithm developments. *Procedia Computer Science*.
- [29] Thi Nha N., Kung-Chin W., En-Cheng Y., Ta-Te L. (2019). A real-time imaging system for multiple Honey Bee tracking and activity monitoring. *Computers and Electronics in Agriculture*. <https://doi.org/10.1016/j.compag.2019.05.050>.
- [30] Vijay G., Amruta A., Vaishali R., Vinayak M., Neha R., Surabhi K. (2024). Smart Beehive Monitoring system using IoT.
- [31] Mirzaei B., Nezamabadi-Pour H., Raoof A., Derakhshani R. (2023). Small object detection and tracking: a comprehensive review. *Sensors*.
- [32] Romero M.J., Quezada-Euan J.J.G. (2013). Pollinators in biofuel agricultural systems: the diversity and performance of bees (Hymenoptera: Apoidea) on *Jatropha curcas* in Mexico. *Apidologie*.
- [33] Ajwin D., Aditya P., Sameer H. (2023). HiveLink, an IoT based Smart Bee Hive Monitoring System.
- [34] Duarte C., Jose M., Henrique S., Frederico B. (2023). BHiveSense: an integrated information system architecture for sustainable remote monitoring and management of apiaries based on IoT and microservices.