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A Practical YOLO Approach to Classifying Thai Freshwater Snails of Economic Significance

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Abstract

Freshwater snails are a valuable economic resource in Thailand, but species identification remains challenging due to morphological similarities that impact pricing, traceability, and aquaculture management. This study assesses an automated freshwater snail classification system using three YOLO variants trained for 100 epochs on 4,610 annotated images of six economically important species. The models were evaluated using precision, recall, mAP50, mAP50–95, inference time, and model size, revealing clear performance trade-offs. YOLOv9-tiny achieved the highest detection accuracy with an mAP50–95 of 0.9738 but incurred the largest model size and slowest inference. In contrast, YOLOv11-nano delivered the fastest inference and smallest footprint, though with lower accuracy (mAP50–95 of 0.8849), making it suitable for resource-limited or edge deployments. YOLOv8 provided a balanced alternative, offering competitive accuracy (mAP50–95 of 0.9708) with moderate computational cost. Misclassification most occurred between Bellamya sp. and Bellamya reticulata, particularly for juvenile specimens, highlighting the difficulty of distinguishing morphologically similar species and the need for more diverse training data. Overall, the results demonstrate the effectiveness of YOLO-based models for automated snail species identification, with strong potential for applications in aquaculture management, market standardization, and supply chain traceability. Future work will focus on real-world deployment, expanding datasets across diverse environments, and integrating explainable AI to improve model transparency and user trust.

Keywords: Thai Freshwater Snails, Automated Species Classification, YOLO Object Detection, Sustainable Aquaculture, Edge Deployment

1. Introduction

Freshwater snails represent an essential yet underappreciated component of Thailand's agricultural and aquatic economy. Beyond their role as a dietary protein source for rural households, they are deeply embedded in a microeconomic network that connects aquaculture, small-scale processing, and local trade [1]. Their economic contribution extends beyond subsistence, providing additional income to smallholder farmers, creating rural employment, and supporting household-based enterprises in food, feed, and fertilizer production. Field reports from northern and northeastern Thailand indicate that community-level producers regularly harvest, process, and sell snail-derived products, including meat and crushed shells, to local agricultural supply markets and feed producers. This illustrates the species' dual value: nutritional and economic. Snails such as Pomacea canaliculata and Filopaludina martensi are commonly marketed in both fresh and processed forms, while shells are repurposed as calcium supplements and soil conditioners. This integration of biological and economic functions underscores their importance to sustainable aquaculture and rural livelihoods.

The biodiversity of economically important snail species—including Pomacea canaliculata, Pomacea spp., Filopaludina martensi, Filopaludina sumatrensis polygramma, Pilsbryoconcha exilis, and Pilsbryoconcha lewisi—offers potential for further development in aquaculture, value-added production, and environmental management [2], [3]. However, the morphological similarity between these species presents a practical challenge for both scientific and

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commercial classification. Many species share overlapping shell coloration, patterns, and curvature, making visual differentiation unreliable without expert verification or genetic confirmation. This has direct consequences for market operations: misidentifying high-value species as lower-value types distorts pricing structures, undermines supply-chain transparency, and reduces farmers' bargaining power. Accurate identification is therefore not only a biological concern but also a socioeconomic one, directly influencing trade fairness, product traceability, and income stability.

Traditional classification methods based on morphological inspection are limited in accuracy and scalability. Manual identification relies on expert taxonomic knowledge and well-preserved specimens under controlled conditions, which are rarely attainable in field settings. In practice, snail shells are often obscured by mud, water stains, and biofilm, and many species share similar shapes, complicating morphological classification. Environmental influences such as habitat and salinity introduce further variation, while the process demands significant time and effort from trained specialists. These difficulties are amplified in complex ecosystems with diverse microhabitats, limiting the reliability, consistency, and scalability of traditional morphology-based approaches. Together, these limitations emphasize the need for molecular or automated classification methods [4], [5], [6], [7], [8], [9]. The resulting inaccuracies contribute to product rejections, inconsistent pricing, and loss of market confidence. In regions where local species co-exist with invasive Pomacea types, morphological confusion may also influence biodiversity assessments and pest control decisions, compounding ecological and economic uncertainties. These issues emphasize the need for an automated, objective, and repeatable classification system capable of functioning under variable field conditions.

Recent advances in computer vision and deep learning have revolutionized image-based classification in agriculture [10], [11], [12] aquaculture, and biodiversity studies [13], [14]. Among modern object detection frameworks, the YOLO (You Only Look Once) family has gained attention for its speed and balance between accuracy and computational efficiency. YOLO's single-stage detection pipeline predicts bounding boxes and class probabilities simultaneously, making it suitable for real-time identification tasks in resource-constrained environments [15]. The architectural evolution from YOLOv8 to YOLOv11 reflects ongoing refinement in feature fusion, loss function optimization, and attention mechanisms that enhance small-object detection. Freshwater snail identification involves fine-grained differences in form and surface texture and is commonly affected by background interference in natural habitats. Although YOLO models have been widely applied with strong results in agricultural and biological studies, their effectiveness has not yet been systematically evaluated on datasets of freshwater snails, resulting in a research gap within the field of aquatic species detection. The broader use of YOLO in practice is also challenged by fluctuating lighting conditions, object obstruction, and the diversity of target species, and progress is further restricted by the dependence on large volumes of carefully annotated training data [16].

This absence of empirical evaluation constitutes a key research gap. Although review articles have examined YOLO architectures in general [15], there is no evidence of practical testing or comparative analysis across YOLOv8, YOLOv9-tiny, and YOLOv11-nano in any mollusk classification context. Moreover, the specific visual complexity of snails—characterized by overlapping shells, reflective surfaces, and irregular patterns—differs significantly from standard datasets such as fruits, insects, or fish used in previous detection studies [17], [18]. Therefore, applying YOLO to this domain requires both empirical validation and methodological adaptation, including field-relevant data collection, species-level labeling protocols, and augmentation strategies that replicate realistic imaging conditions. Addressing this gap would contribute both technically, by establishing baseline performance metrics, and practically, by enabling accurate species recognition that supports smallholder aquaculture and trade management.

The current study builds upon this gap by proposing a data-driven framework that combines applied computer vision with aquaculture science. Instead of developing new architectures, the study focuses on evaluating and comparing the detection performance of three recent YOLO variants—YOLOv8, YOLOv9-tiny, and YOLOv11-nano—on a purpose-built dataset of six economically important freshwater snail species. Each model offers a distinct trade-off between detection accuracy, inference speed, and computational cost. YOLOv8 provides a balanced configuration for general use; YOLOv9-tiny is optimized for edge devices with limited processing resources; and YOLOv11-nano represents the newest lightweight design emphasizing inference efficiency and stability [19]. Evaluating these models under standardized training and testing conditions provides insights into their real-world applicability for aquaculture operations, including on-site sorting, quality control, and biodiversity monitoring.

The integration of YOLO-based detection into aquaculture practice also addresses practical field challenges. In environments such as smallholder farms, markets, and hatcheries, classification systems must handle inconsistent lighting, reflections, and muddy surfaces while maintaining accuracy and speed. A reliable model can support several use cases: guiding selective breeding by species, preventing unintentional cross-contamination between edible and pest snails, and improving labeling accuracy in local trade. Real-time image classification could also serve as a foundation for traceability systems and certification processes, allowing producers to verify species authenticity before distribution. By linking digital identification with existing farming workflows, this technology could reduce manual workloads and human error, while generating structured data for management and research. These functions demonstrate that AI-based classification has immediate relevance to field operations rather than serving only as a theoretical contribution.

From a methodological standpoint, the study emphasizes reproducibility and transparency. Data were collected under natural farm and market conditions using multiple cameras and angles to capture realistic variability. Annotation protocols distinguish between genus-level and species-level certainty to reduce labeling bias. Training procedures apply identical hyperparameters across models, including optimizer, batch size, and input resolution, ensuring that performance differences arise from architecture rather than tuning. Evaluation metrics—mean average precision (mAP), precision, recall, training time, and inference speed—are selected to reflect both algorithmic quality and practical usability in low-resource environments. This rigorous design ensures that benchmarking results are scientifically valid and directly interpretable for real-world deployment.

The implications of such work extend beyond academic interest. In regions where snail farming and harvesting contribute significantly to rural economies, reliable species identification can strengthen regulatory compliance, traceability, and market transparency. Accurate classification supports the development of labeling standards, enabling buyers and certification agencies to verify product authenticity and prevent disputes. On the ecological side, improved identification helps monitor invasive species and supports conservation planning. These multifaceted benefits make freshwater snail classification not just a niche technical problem but a linchpin for sustainable aquaculture systems in Southeast Asia.

The primary objective of this research is to develop and evaluate an AI-based automated framework for accurate, field-adaptable classification of freshwater snails using YOLO architectures. Specifically, the study aims to (1) construct a representative image dataset encompassing environmental and morphological variability; (2) benchmark YOLOv8, YOLOv9-tiny, and YOLOv11-nano under identical conditions to determine comparative strengths; and (3) analyze model performance trade-offs between accuracy, inference speed, and computational resource requirements. The overarching goal is to identify the most practical YOLO variant for deployment in aquaculture and trade contexts while contributing baseline data for future research on automated species identification and biodiversity monitoring. Through this, the study seeks to bridge the gap between AI model performance and its tangible value in supporting sustainable freshwater snail production and rural economic resilience.

2. Literature Review

2.1. Economic and Societal Importance of Thai Freshwater Snails

In Southeast Asia, freshwater snails are an essential component of inland aquatic biodiversity. They inhabit habitats such as rivers, wetlands, and rice paddies in many countries, including Thailand, Vietnam, and Indonesia [13], [14]. Ecologically, snails play a role in nutrient cycling and prey on higher organisms such as fish and birds [14]. Culturally and nutritionally, snail meat is an integral part of regional diets, with their muscles and organs rich in protein and unsaturated fats [14], [18]. Indeed, snail consumption is a prominent feature of Asian culinary culture [18], and snail meat products and by-products are increasingly regarded as valuable ingredients in the food industry. As a result, Southeast Asia is characterized by a high snail diversity and a growing economic interest in the utilization of snails.

Snails also play a significant economic and social role. Their meat has high nutritional value, being rich in amino acids and calcium [18], and can be sold as food. In practice, snail meat and flour are being tested and used as animal feeds across Asia. For example, Yao et al. [19] demonstrated that golden apple snail (Pomacea canaliculata) flour can replace up to 50% of fish meal in the diet of juvenile mud crabs without negatively affecting their growth or health. Similarly, minced native snails are used as a protein-rich feed in small fish and duck farms in Bangladesh [14], indicating similar potential in Thailand. Snail shells are also valuable, for instance, as a calcium source for animal feed or even as a food ingredient [14]. Therefore, the uses of freshwater snails throughout their life cycle provide both environmental and direct economic benefits, emphasizing their multi-faceted importance.

A notable example is a recent study showing that flour from the apple snail (Pomacea canaliculata) can replace a large portion of commercial protein feeds. The use of apple snail meat (PCM) to provide 50% of dietary protein did not significantly impact the growth, immunity, or gut health of farmed hairy crabs [19]. In practice, this indicates that snail farms in Thailand can supply both food and valuable feed ingredients. Snail biomass is plentiful and contains about 60% unsaturated fat, along with high levels of calcium and magnesium [8], making it suitable for processing into snail flour. Commercial snail farms have the potential to produce snails year-round. Some reports suggest that snails can be harvested within 5–7 months of cultivation, which could improve local food security and increase income [19].

For this reason, Thai freshwater snails are economically and socially significant in many ways, including their environmental role in maintaining biological balance, their nutritional value as a high-quality protein source, and their contribution to the economy. Freshwater snails are a major income source through their cultivation and processing into food and animal feed. Therefore, modern research supports that proper conservation and utilization of freshwater snails can help improve food security and sustain the local economy of Thailand.

2.2. YOLO Evolution and Architecture

The YOLO (You Only Look Once) family has undergone significant architectural evolution from YOLOv8 to YOLOv11, driven by the need to balance detection accuracy, inference speed, and computational efficiency. According to an architectural review covering YOLOv8–YOLOv11, the overall backbone–neck–head pipeline remains consistent across versions, but each release introduces new feature fusion modules, optimized loss functions, and structural refinements intended to improve real-time performance [17]. YOLOv8, for example, extends concepts from YOLOv5 by incorporating the C2f module to enhance multi-scale feature representation while reducing parameter overhead, together with updates to loss design for improved detection stability, particularly for small objects [17].

YOLOv9 introduces additional architectural mechanisms such as GELAN (Generalized Efficient Layer Aggregation Network) and PGI (Programmable Gradient Information) to improve gradient propagation and feature aggregation without increasing computational cost substantially. These updates are intended to address issues such as vanishing gradients and uneven layer contribution during training, especially in lightweight variants optimized for embedded devices [20].

YOLOv11 builds upon previous versions by integrating updated components such as the C3k2 block, SPPF (Spatial Pyramid Pooling – Fast), and C2PSA (Parallel Spatial Attention), which target improved feature extraction under conditions involving occlusion, object overlap, or fine-grained visual details. Architectural overviews report that YOLOv11 offers improved accuracy–efficiency trade-offs across its nano to extra-large variants, making it adaptable to both high-performance hardware and edge-level deployment [21].

The progression from YOLOv8 to YOLOv11 reflects a design trend toward reduced redundancy, modular feature fusion, and increased suitability for resource-constrained environments. However, these evaluations are based on architectural characteristics rather than empirical benchmarking. To date, no prior study has assessed the comparative performance of YOLOv8, YOLOv9-tiny, and YOLOv11-nano on freshwater snail classification tasks, making the present work the first experimental evaluation of these models in this domain.

2.3. YOLO for Aquatic Species Classification

Detection and classification of aquatic animals face different challenges compared to conventional object detection tasks. Underwater environments often encounter issues such as light attenuation, color distortion, variable illumination, small particles like suspended matter, and occlusion caused by organism groups, all of which degrade image quality and lower the signal-to-noise ratio. Recent research aims to adapt YOLO and its lightweight models to address these challenges. For example, the LFN-YOLO model introduces a new lightweight parameterization method specifically for detecting small objects in underwater scenes, utilizing multi-scale feature integration to enhance the detection of low-contrast, small underwater targets. Liu et al. (2025) reported that LFN-YOLO significantly boosts the detection of small underwater objects by balancing detection accuracy (mAP) and computational efficiency. Similarly, AGS-YOLO (Sun et al. 2025) enhances YOLO11 with Multi-Scale Attention (AMSA) and an optimized C3k2 module, along with a simplified neck network (CSFE) and a GSConv module to decrease computational load while achieving better accuracy on small underwater datasets. Studies indicate that AGS-YOLO outperforms the baseline YOLO11-nano in both mAP@0.5 and mAP@0.5:0.95 on challenging underwater datasets [22].

The lightweight sensing model approach, Mobile-YOLO, proposed by Jiang et al., provides clear direction for field applications. By combining the Mobile-Nano microbackbone with the LDtect detector head and Dysample mechanism, along with Haar wavelet resampling (HWD), it can maintain the structural resolution of objects while effectively reducing computational load. The resulting mAP of approximately 82.1%, combined with a high frame rate and fewer parameters/FLOPs, demonstrates that the design concept of "preserving important signals and trimming unnecessary ones" is practical for a diverse range of marine organisms [23]. When applied to freshwater mollusk classification, HWD may help capture key shell pattern and texture details for species differentiation, while Dysample preserves important features when working with compressed or occluded images. Furthermore, the lightweight detector design enables multi-tasking functions, such as classification combined with counting and sizing, which can still be performed on edge devices, allowing small farms to access real-time monitoring without relying on cloud. The next challenge is to integrate field-specific augmentation strategies and hardware–software co-design to ensure that the model remains robust across different angles, sample groups, and lighting conditions. This involves measuring practical indicators such as energy per image and time-to-decision to assess their suitability for real-world applications in freshwater mollusk aquaculture systems and supply chains [23].

The Dynamic YOLO approach, which employs deformable convolution as its core and combines multi-level features with channel-wise, scale-wise, and spatial attention to fuse multi-scale feature maps, introduces a new dimension in detecting small underwater objects. These objects are often obscured by sediment, scattered light, or water movement. Deformable convolution enables the filter to be flexible with distorted shapes and irregular details, while attention fusion highlights important signals from multiple scales at the same time. The result is improved sensitivity for detecting small objects while preserving the spatial quality of the features. For freshwater mollusk classification, this method can be extended to include temporal aggregation to reduce motion noise, incorporate optical flow or motion cues to separate moving objects from static scenes, and develop augmentations that simulate water turbidity and shell stains to make the model more robust in real-world field conditions. Additionally, the use of adaptive attention allows for the development of lightweight, multi-task heads to measure size and confidence alongside classification. This enables Dynamic YOLO not only to enhance accuracy in challenging environments but also to be efficiently integrated into pipelines running on edge devices with low energy consumption [24].

Practical aquaculture applications of YOLO variants demonstrate a clear pathway from laboratory-level accuracy to field-ready automation; for instance, FishDETECT enhanced YOLOv5 through transfer learning and FishMask pre-training to reliably classify fish in challenging conditions—such as low light, clutter, and diverse backgrounds—achieving outstanding mAP50, precision, and recall (approximately 0.995, 0.962, 0.978), thereby surpassing simpler baseline models [25]. Similarly, an automated sorting system utilizing YOLOv4 identified eight freshwater fish species on conveyor belts with approximately 98.15% accuracy, exemplifying how controlled pipelines can attain remarkably high operational performance [26]. These achievements underscore two complementary strategies pertinent to snail aquaculture: firstly, targeted pre-training and transfer learning on domain-specific masks or synthetic scenes can substantially enhance robustness against visual noise and occlusion; secondly, the integration of detection models into comprehensive pipelines—including imaging, mask generation, classification, and mechanical sorting or tagging—can convert per-image accuracy into reliable, high-throughput farm operations. Applying this methodology to snail systems offers immediate advantages—including automated grading, real-time yield estimation, and swift quality assessments—while concurrently addressing engineering requirements such as domain-specific augmentation, calibrated confidence thresholds for human-in-the-loop verification, and lightweight inference suitable for edge devices, thereby ensuring that the high accuracies achieved in fish systems remain practical and accessible for smallholder snail farmers [25], [26].

While the enhancements of YOLOv4-Tiny substantially improve inference speed and accuracy for underwater biosensing, experiments underscore its frailty when confronted with cluttered or occluded scenes, conditions prevalent in real-world aquaculture systems. Sacrificing some feature resolution for speed constrains the capability to detect and isolate small or occluded objects. Innovative strategies to mitigate this trade-off may include designing a two-tier pipeline that integrates a lightweight real-time model with a higher-capacity on-demand model for low-confidence scenarios; incorporating temporal aggregation and multi-frame fusion to diminish noise caused by water movement; utilizing domain-specific preprocessing techniques such as dehazing and contrast enhancement suitable for turbid underwater conditions; and integrating spectral or depth sensors to supplement spatial information. These initiatives can preserve processing speed while enhancing robustness against clutter and occlusion, thereby enabling aquaculture-focused systems to deliver more practical and reliable detections in field environments [27].

The current body of work indicates a promising convergence: attention-enhanced feature fusion, deformable and multi-scale backbones, and carefully designed lightweight architectures can all provide strong detection performance for small and visually challenging aquatic taxa. Domain-specific augmentation and pre-training further enhance robustness in noisy, cluttered scenes [14]–[18]. What still remains absent—and what would most speed up practical adoption—is a systematic, head-to-head benchmarking of the latest YOLO models (v8, v9-tiny, v11-nano) on standardized, field-collected datasets that capture the quirks of snail farming, such as occlusion, wet surfaces, grouped samples, variable lighting, and low connectivity. Such a study should evaluate not only mAP and FPS but also energy-per-inference, model size, calibration/uncertainty, and real-world decision time. It should also assess hybrid pipelines that combine an ultra-light front-end for continuous screening with a higher-capacity back-end for on-demand re-inspection—an architecture that balances the speed/accuracy tradeoffs highlighted by YOLOv4-Tiny improvements and FishDETECT successes [16], [18]. Complementary strategies—transfer learning from domain masks, attention-guided heads for texture discrimination, motion-aware temporal fusion, and active learning loops that involve farmers for targeted labeling—would bridge the gap between academic benchmarks and farm-level utility. These approaches would enable explainable, low-resource deployments that truly improve pricing transparency, traceability, and conservation outcomes in snail aquaculture.

3. Materials & Methods

3.1. Research Framework and Design

The research framework was developed to systematically guide the process of applying an AI-driven YOLO model for the automated classification of Thai economic freshwater snail species. It begins with data collection and preprocessing to ensure high-quality image inputs, followed by model training and validation using a deep learning architecture tailored for object detection. The design emphasizes both scientific rigor and practical applicability, ensuring that the outcomes are reliable for ecological and economic contexts.

In this study, the YOLOv8, YOLOv9-tiny, and YOLOv11-nano architectures are applied as the main framework for automated classification of freshwater snail species. The workflow begins with image preprocessing through resizing, normalization, and augmentation to ensure data quality. The backbone extracts essential features, the neck aggregates information at multiple scales, and the head produces bounding boxes, confidence scores, and class predictions for accurate identification.

With improvements in feature extraction, anchor free detection, and optimized training, models achieve high accuracy while maintaining real time performance. This framework provides a reliable approach for ecological monitoring and the classification of Thai economic freshwater snail species. It is illustrated in figure 1.

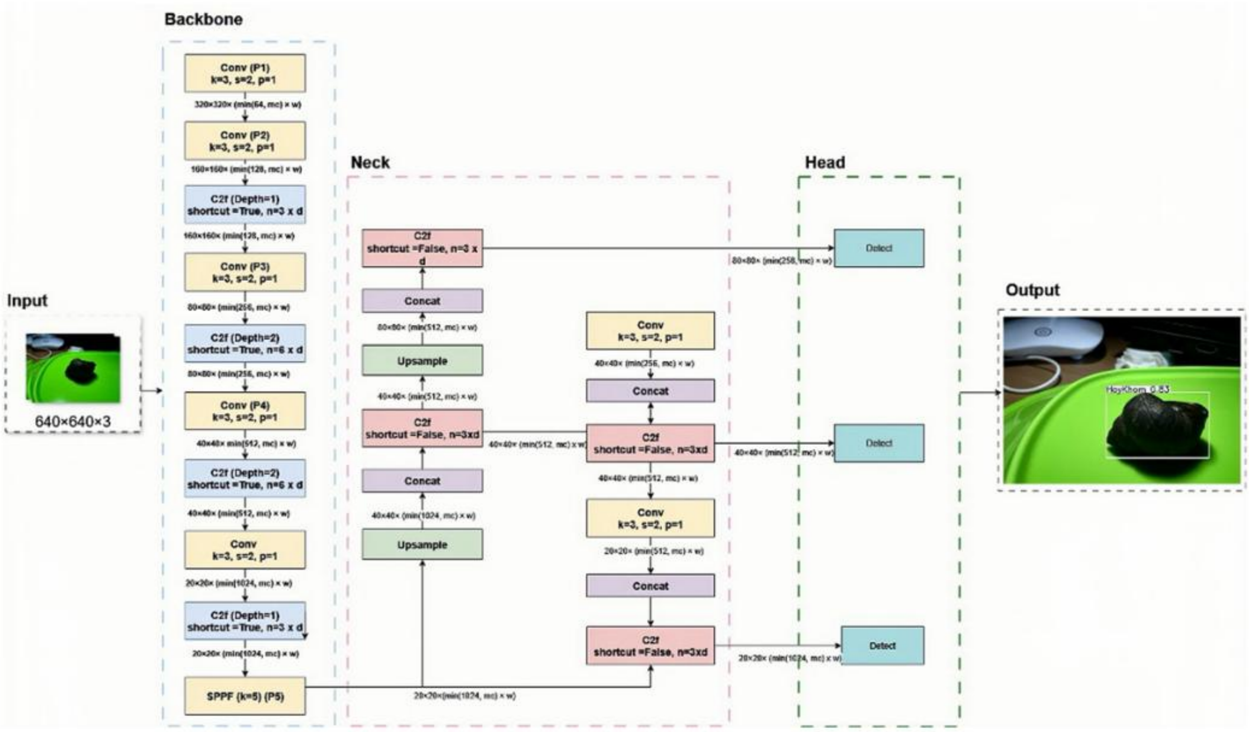

Figure 1. YOLO-based Deep Learning Architecture for Thai Economic Freshwater Snail Classification. [15]

The research framework illustrated in Figure 1 represents the full operational pipeline of the proposed automated snail classification system, beginning with raw image acquisition and ending with model-generated species predictions. The YOLO architecture adopted in this study follows a standard three-stage design consisting of a Backbone, Neck, and Detection Head. The Backbone performs hierarchical feature extraction through stacked convolutional layers and C2f modules, enabling the model to encode shell morphology, surface texture, and geometric cues across multiple spatial resolutions. The Neck aggregates multi-scale representations through a combination of Feature Pyramid Network and Path Aggregation Network structures, allowing the detector to remain stable under real-world imaging variations, including scale differences, occlusion, and mud-induced visual noise. Finally, the Head applies an anchor-free prediction mechanism to generate bounding boxes, class labels, and confidence scores in a single forward pass, which is essential for real-time or embedded applications.

The structure shown in the figure is not merely an architectural diagram but a visual representation of the methodological pipeline implemented in this study. It aligns with the experimental workflow, including field-based data collection, dual-annotator labeling, dataset partitioning, model training under controlled hyperparameters, and performance benchmarking across YOLOv8, YOLOv9-tiny, and YOLOv11-nano. The evaluation metrics—mAP, precision, recall, inference latency, and model size—were selected to reflect both algorithmic performance and deployment feasibility, particularly in low-resource environments such as mobile aquaculture monitoring systems or edge-based quality-control units. The framework therefore bridges computational modeling with practical aquaculture challenges, positioning the study not only as a computer-vision benchmark but also as an enabling step toward data-driven decision tools for economic species management.

3.2. Study Species and Sample Collection

This study focused on six economically important freshwater snail species in Thailand, selected for their high aquaculture value and morphological diversity.

Specimens were collected from farms and natural habitats across Thailand to capture variability in shell morphology, color, growth stage, and surface condition. For the genus Pomacea, an operational taxonomy was applied to prevent label overlap during model training. The class Pomacea canaliculata was assigned only to individuals whose diagnostic species-level traits (such as apical shape, shell lip structure, and ridge pattern) were clearly identifiable and confirmed by expert annotators. In contrast, Pomacea spp. was used for individuals belonging to the genus Pomacea for which

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species-level confirmation was not possible from images due to juvenile size, abrasion, occlusion, or incomplete viewpoints. This reflects real-world aquaculture and market conditions, where product classification often distinguishes confirmed P. canaliculata from mixed or uncertain Pomacea stock.

Specimens were collected from ten aquaculture farms and natural freshwater habitats in Thailand to capture variability in shell morphology, color, and size. Each snail was photographed under controlled lighting to ensure clear visibility of identifying features.

The dataset was stored in image format, totaling 10.76 GB and consisting of 4,610 images. All photographs were captured using an iPhone 13 Pro, equipped with a triple rear camera system (12 MP wide, 12 MP ultra-wide, and 12 MP telephoto). This setup provided high-resolution images with sufficient clarity to enable precise annotation and effective models. Example images from the freshwater snail dataset in figure 2. The detailed composition of the dataset, including the number of images for each snail species class, is summarized in table 1.

Figure 2. Example images from the freshwater snail dataset

Table 1. Dataset composition of freshwater snail species

No	Snail Species	Images
1	Field Cherry Snail (Pomacea spp.)	1,163
2	Golden Cherry Snail (Pomacea canaliculata)	940
3	Freshwater Pomacea Snail (Bellamya sp.)	888
4	Giant Pomacea Snail (Bellamya reticulata)	783
5	Elongated Mussel (Pilsbryoconcha exilis)	445
6	Round Mussel (Pilsbryoconcha lewisi)	391
	Total Images	4,610

3.3. Image Dataset Preparation

High-resolution images of each species were captured using digital cameras to ensure variation in morphology, color, and size suitable for model training. All images were annotated in YOLO Darknet format through a two-stage labeling process in which two independent annotators assigned species labels, followed by adjudication when disagreement occurred. For Pomacea canaliculata, labeling was restricted to cases where species-diagnostic traits were visible in at least two perspectives or high-resolution shell segments. Specimens in which species-level traits could not be confirmed because of juvenile morphology, abrasion, mud coverage, occlusion, or incomplete orientation were assigned to the Pomacea spp. class to prevent taxonomic overlap. Inter-annotator agreement was measured using Cohen's kappa, and samples with low confidence were retained for optional relabeling in a future active-learning workflow. Standard YOLO augmentations, including flipping, rotation, translation, and scaling, were applied to increase visual diversity and reduce overfitting. The dataset was then divided into training, validation, and test sets at a ratio of 70, 15, and 15 percent.

Only geometric and photometric augmentations were applied in this phase of the study. More complex farm-specific augmentations such as mud overlays, water surface reflections, variable lighting, and background turbidity were intentionally excluded. This decision was made to establish a controlled experimental baseline before introducing environment-specific distortions that could confound model comparison. Domain-realistic augmentation will be integrated in subsequent phases, once the core performance characteristics of each YOLO model have been benchmarked under standard conditions.

The dataset contains a moderate class imbalance, with Pilsbryoconcha lewisi represented by 391 images compared with 1,163 images for Pomacea spp., the largest class. No oversampling, loss reweighting, or synthetic balancing methods were used; all classes received identical augmentation procedures. The reported performance metrics therefore reflect the natural distribution of the dataset rather than a balanced training regime and may favor majority classes. Future extensions of this work will include class-weighted learning or targeted augmentation to address this imbalance and to evaluate whether minority-class performance improves under balanced training conditions.

3.4. YOLO Model

For the automated detection and classification of freshwater snail species, three variants of the YOLO architecture—YOLOv8, YOLOv9-tiny, and YOLOv11-nano—were selected for evaluation in this study. These models follow the one-stage object detection paradigm, in which bounding box localization and class prediction are performed in a single pass, enabling real-time inference suitable for field deployment and resource-constrained environments. Architecturally, YOLOv8 introduces the C2f module for improved multi-scale feature extraction, YOLOv9-tiny incorporates GELAN and PGI to enhance gradient flow in lightweight configurations, and YOLOv11-nano applies components such as C3k2 and SPPF to improve spatial representation while maintaining a minimal model footprint [15]. These descriptions reflect the architectural designs reported in prior literature rather than empirical performance outcomes.

In this study, the three models were trained under identical conditions, including an input resolution of 640×640, batch size of 16, standard augmentation, and 100 training epochs. Their performance—measured in terms of precision, recall, mean average precision, model size, and inference time—was evaluated experimentally using the freshwater snail dataset developed in this work. The comparative results presented in the following sections therefore reflect benchmarking conducted in this study, as no prior research has assessed these YOLO variants on freshwater snail classification.

3.5. Model Training and Evaluation

All three YOLO models were trained under a unified hyperparameter configuration to ensure that performance differences reflected architectural behavior rather than optimization bias. Training was conducted for 100 epochs using the Adam optimizer with an initial learning rate of 0.001, momentum of 0.937, and a weight decay value of 0.0005. A cosine learning-rate scheduler with a three-epoch warmup phase was applied to stabilize early convergence, while gradient clipping and mixed-precision (FP16) training were enabled to control numerical instability and reduce GPU memory usage. The input resolution was fixed at 640×640 pixels, with a batch size of 16, and the same augmentation pipeline was applied across all models. No model-specific hyperparameter tuning was performed, since the objective was to evaluate relative model performance under identical training constraints.

The dataset was partitioned into 70 percent training, 15 percent validation, and 15 percent testing splits while preserving class stratification. Model performance was evaluated using precision, recall, F1-score, mAP@50, mAP@50–95, inference time, and model size, together with class-wise analysis to examine behavior on minority and visually ambiguous classes. Particular attention was given to the distinction between Pomacea canaliculata and Pomacea spp., which represents an operational classification boundary rather than a strict taxonomic division. Confusion matrices and precision–recall curves were generated to characterize error patterns and to identify cases in which visual ambiguity, occlusion, or juvenile morphology led to systematic misclassification.

To examine prediction reliability beyond raw accuracy, calibration analysis was performed using Expected Calibration Error (ECE), and predictions with confidence below 0.60 were flagged as referral-required samples, reflecting realistic deployment scenarios in which uncertain cases must be escalated to human review or molecular validation. All reported

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results are based exclusively on experimental data from this study, as no prior benchmarking of YOLOv8, YOLOv9-tiny, or YOLOv11-nano exists for freshwater snail classification. This controlled setup provides a reproducible technical baseline from which future model tuning, statistical validation, and deployment-oriented optimization can proceed. Figure 3 illustrates the end-to-end training and testing process flow, starting from dataset creation, followed by model training and validation, and concluding with model testing to produce the final output.

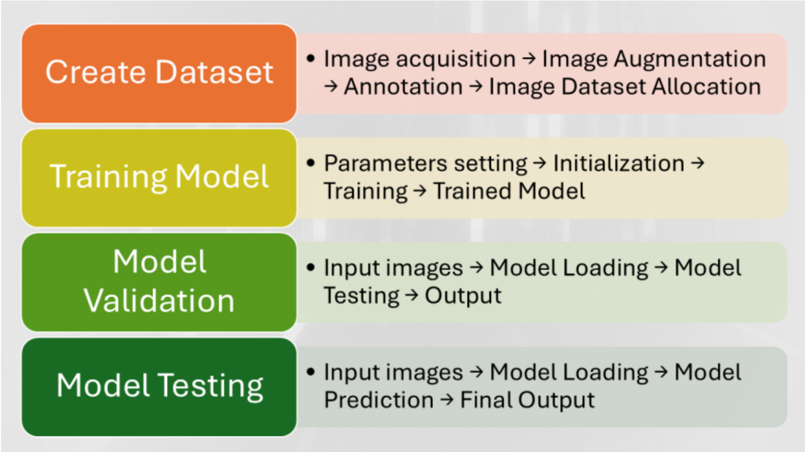

Figure 3. Training and Testing process flow

4. Results and Discussion

4.1. Model Development

YOLOv8, YOLOv9-tiny, and YOLOv11-nano were trained for freshwater snail classification over 100 epochs using input size 640×640, batch size 16, an initial learning rate of 0.003→0.00002, and standard augmentation (scaling, flipping, color jitter). The models optimized a combined loss for localization, classification, and confidence, with validation data guiding hyperparameter adjustment to avoid overfitting.

Model settings balanced accuracy and efficiency: YOLOv8 prioritized speed and stability, YOLOv9-tiny delivered the highest accuracy with higher computational cost, and YOLOv11-nano offered lightweight yet robust performance. All experiments were run on Google Colab Pro (NVIDIA Tesla T4 GPU, 16 GB; 25 GB RAM; 100 GB storage), ensuring efficient training and reliable convergence across 100 epochs.

Figure 4 presents the training and validation loss trends of three models: YOLO v8, YOLOv9-tiny, and YOLOv11-nano. For all models, the training losses for bounding box regression, classification, and distribution focal loss decrease steadily across epochs, indicating effective convergence. The validation losses follow a similar pattern, confirming good generalization performance. Among the models, YOLOv9-tiny attains the lowest and most stable losses, especially in box regression and classification, demonstrating superior accuracy. YOLOv8 shows a smooth and consistent loss reduction, while YOLOv11-nano converges more slowly, likely due to its smaller parameter count and limited model capacity. All models achieve high precision and recall, generally above 0.90 during training. YOLOv9-tiny delivers the highest and most stable precision, while YOLOv8 attains comparable recall, reflecting strong detection capability. YOLOv11-nano shows lower recall, likely due to missed detections in complex or occluded scenes, which is typical for lightweight models.

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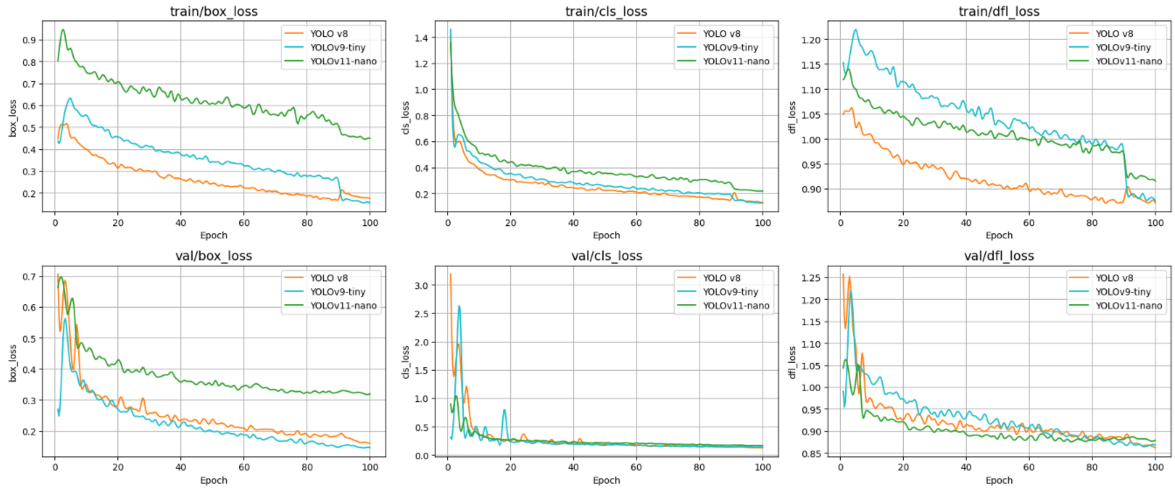

Figure 4. Training and Validation Loss Comparison Across Models

Figure 5 illustrates the mAP at IoU 0.5 and 0.5 to 0.95 across training epochs. YOLOv9-tiny achieves the highest scores in both metrics, followed by YOLOv8. YOLOv11-nano records lower mAP values, consistent with its nano-scale design that favors efficiency over detection accuracy.

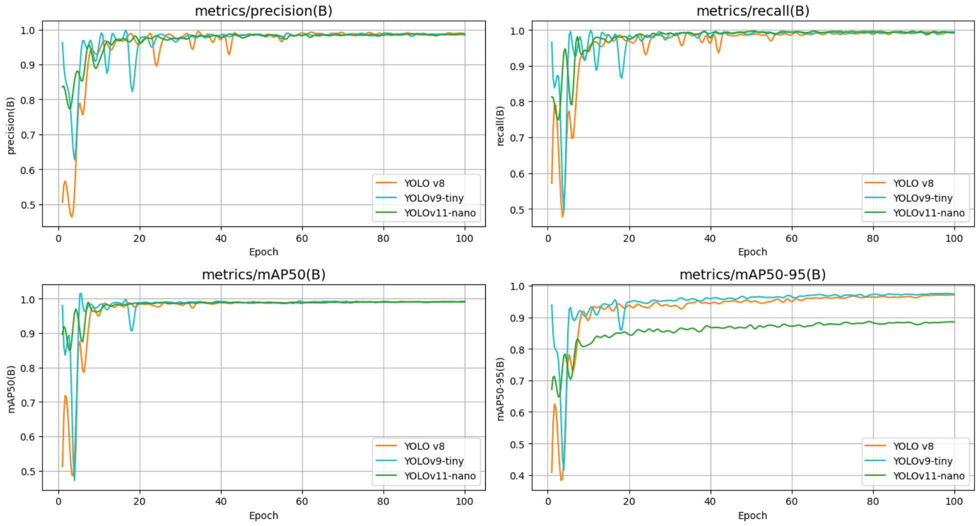

Figure 5. Performance Metrics Comparison

Figure 6 shows example results from the validation set that reflect the model's detection capability. The visual outputs indicate accurate localization and classification with high confidence, reinforcing the reported performance metrics and demonstrating robust generalization in realistic conditions.

Figure 6. Sample Data Validation Output

4.2. Model Performance Evaluation

To evaluate the performance of the developed models, researchers assessed detection accuracy and computational efficiency. Key metrics for YOLOv8, YOLOv9t, and YOLOv11-nano including precision, recall, mAP, inference time, and model size are summarized in table 2, highlighting the strengths and trade-offs of each model.

Table 2. Model Performance Evaluation

Model	Precision	Recall	mAP50	mAP50–95	Loss (Box / Cls)	Inference Time (ms)	Model Size (MB)
YOLOv8	0.9883	0.9904	0.9904	0.9708	0.1589 / 0.1240	2549.19	49.6
YOLOv9-tiny	0.9871	0.9935	0.9917	0.9738	0.1455 / 0.1379	4452.05	111.8
YOLOv11-nano	0.9848	0.9930	0.9904	0.8849	0.3193 / 0.1638	1513.33	38.6

Table 2 provides a quantitative comparison of the three models in terms of detection accuracy, loss, computational cost, and model size. All models achieve precision and recall above 0.98, confirming strong detection reliability. YOLOv9-tiny records the highest mAP@0.5 and mAP@0.5–0.95, together with the lowest box loss, indicating superior localization performance, though at the expense of increased inference time and larger model size. YOLOv8 delivers comparable accuracy with lower computational overhead and stable loss values, offering balanced performance.

By contrast, YOLOv11-nano emphasizes efficiency, achieving the smallest footprint and fastest inference. Despite maintaining high precision and recall, its lower mAP@0.5–0.95 and higher losses suggest reduced localization accuracy under stricter IoU conditions, reflecting its limited capacity. Overall, the results underline the trade-off between accuracy and efficiency, positioning YOLOv9-tiny for accuracy-focused tasks, YOLOv8 for balanced applications, and YOLOv11-nano for resource-limited or real-time deployment. As summarized in table 3, the comparative results reveal a clear trade-off between training cost and inference efficiency among the YOLO variants, highlighting how model size and architectural design differently impact training duration and deployment performance.

Table 3. Comparative Training and Inference Performance of YOLO Models

Model	Parameters (M)	Train Time / Epoch (sec)	Total Train Time (100 epochs)	Inference Time (ms/img)
YOLOv8	11.1M	96	9,600s	2549 ms
YOLOv9-tiny	24.7M	520	52,000s	4452 ms
YOLOv11-nano	6.3M	1350	135,000s	1513 ms

A clear divergence emerges between training duration and inference efficiency across the three YOLO variants. Although YOLOv11-nano has the smallest parameter count (6.3M) and delivers the fastest inference time (1,513 ms/image), it requires the longest total training time, taking 1,350 seconds per epoch—substantially slower than both YOLOv8 and YOLOv9-tiny. In contrast, YOLOv8 shows the shortest training time per epoch (96 seconds) and the lowest total training cost, but its inference latency is almost twice that of YOLOv11-nano. YOLOv9-tiny exhibits intermediate behavior in terms of model size but is slower than both alternatives in inference, despite training faster than YOLOv11-nano. These results indicate that inference speed is strongly correlated with parameter count, whereas training time is influenced not only by model size but also by implementation factors such as optimizer configuration, memory access efficiency, and augmentation load. Consequently, model selection for deployment should not assume that lightweight architectures guarantee fast training, and benchmarking must separately evaluate training cost and inference performance rather than treating them as interchangeable indicators.

5. Discussion

The results highlight clear performance differences among the models, reflecting the trade-offs between accuracy, computational cost, and model complexity. All models achieve high precision and recall, confirming the robustness of the detection framework and the effectiveness of the training strategy.

YOLOv9-tiny delivers the highest detection accuracy, particularly in mAP@0.5 and mAP@0.5–0.95, indicating superior localization but at the expense of higher computational demands. YOLOv8 offers a well-balanced alternative, achieving comparable accuracy with lower inference cost and stable convergence. In contrast, YOLOv11-nano prioritizes efficiency, providing fast inference and compact size, though with reduced localization accuracy under stricter IoU thresholds. Overall, model selection should be guided by application needs, balancing accuracy requirements against resource constraints.

Model behavior across classes shows that most misclassifications occurred between Pomacea canaliculata and the more generic Pomacea spp. class. These errors involved specimens with incomplete visibility of diagnostic features, including juveniles, mud-covered shells, and single-angle views lacking species-level markers. The distinction between the two classes therefore reflects an operational labeling strategy rather than a strict taxonomic separation, ensuring that uncertain samples are intentionally captured in a non-specific category. A hierarchical or confidence-aware classification pipeline may further reduce such errors by routing ambiguous cases to secondary verification rather than forcing species-level predictions.

Misclassification among Bellamya sp. and Bellamya reticulata suggests that classification errors arose not only from visual similarity in shell pattern and curvature but also from potential annotation uncertainty, since field identification relies on subtle traits not always visible in a single image. This reinforces that model accuracy is bounded partly by the limits of available visual information rather than architecture alone. Improvements in performance will likely require multi-view imaging, metadata inclusion, or hybrid workflows that incorporate manual checks or molecular verification when confidence falls below a threshold.

The differences in training and inference behavior also require careful interpretation. Although YOLOv11-nano has the smallest model size (38.6 MB) and fastest inference time (1513.33 ms), it required the longest training duration (1350 seconds per epoch). This does not contradict its suitability for edge deployment, since training costs are incurred only once on high-performance hardware, whereas deployment concerns inference efficiency and memory footprint. The longer training time resulted from the specific experimental configuration, including slower convergence settings and heavier augmentation, rather than architectural inefficiency. Once trained, YOLOv11-nano remains the most suitable model for resource-constrained hardware, while YOLOv9-tiny and YOLOv8 serve higher-capacity or latency-tolerant environments.

However, the reported performance metrics represent single-run point estimates and do not include confidence intervals or statistical significance testing. Because the dataset is moderately imbalanced—ranging from 391 samples for Pilsbryoconcha lewisi to 1,163 for Pomacea spp.—results may favor majority classes, and superiority claims among models should be interpreted cautiously. Future work will incorporate repeated training runs, per-class error analysis, and statistical testing to determine whether observed differences remain significant under controlled variance.

Finally, although the study provides a validated technical foundation for automated classification, no user-facing interface, explainability module, or human-in-the-loop mechanism has yet been implemented. Features such as Grad-CAM visualizations, uncertainty prompts, or farmer-oriented dashboards remain conceptual rather than operational. Therefore, the system should not be regarded as deployment-ready; instead, it represents the first phase in a multi-stage pipeline. Subsequent work will develop an explainable interface, integrate field validation, and evaluate adoption feasibility in real aquaculture settings to bridge the gap between laboratory performance and practical economic impact.

To clarify the proposed hybrid verification framework, molecular identification is not positioned as a replacement for computer vision but as a secondary validation route for low-confidence detections produced by the YOLO model. In practice, specimens flagged below a confidence threshold (e.g., 0.60) would be routed to a verification workflow in which tissue or shell-surface swabs are collected for DNA barcoding based on mitochondrial COI markers, which are commonly used for species-level discrimination in mollusks. The resulting molecular labels can then be fed back into the training pipeline as high-certainty annotations, enabling an active-learning loop that reduces future ambiguity. This establishes a concrete integration point between the image-based detector and molecular confirmation instead of a purely speculative future direction.

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6. Conclusion

Freshwater snails are economically important in Thailand, yet their visual similarity across species continues to hinder accurate classification in farming, trading, and regulatory contexts. The application of deep learning offers a scalable alternative to manual inspection, but its effectiveness depends not only on model accuracy in controlled settings but also on its robustness when deployed under real farming conditions. This study evaluated three YOLO variants—YOLOv8, YOLOv9-tiny, and YOLOv11-nano—using a field-collected dataset to establish a technical baseline for automated species recognition. This work evaluates three object detection models, YOLO v8, YOLOv9-tiny, and YOLOv11-nano, using precision, recall, mAP at IoU 0.5 and 0.5–0.95, and validation loss over 100 training epochs. Quantitative comparisons highlight distinct performance characteristics among the models.

YOLOv9-tiny achieves the highest overall accuracy with the best mAP@0.5–0.95, supported by strong precision and recall, indicating robust localization and classification at the cost of higher complexity. YOLO v8 provides a balanced alternative, delivering competitive accuracy with improved efficiency, making it suitable for general-purpose applications. YOLOv11-nano emphasizes efficiency and attains high recall but shows lower mAP and higher validation loss, reflecting limited generalization due to reduced model capacity. Overall, YOLOv9-tiny suits accuracy-critical tasks, YOLO v8 balances speed and performance, and YOLOv11-nano is appropriate for resource-constrained environments.

The present work should be regarded as a foundational phase in a longer development pipeline rather than a complete deployment-ready system. The study focuses on model benchmarking and does not yet include an explainable interface, farmer-oriented usability testing, or human-in-the-loop decision support. Future work will expand the dataset to address class imbalance, incorporate statistically controlled evaluation, and develop an operational interface with confidence-based referral mechanisms for ambiguous cases. These steps will be necessary to move from model accuracy toward real-world adoption in aquaculture and trade environments.

7. Limitation

A key limitation of this study is that the reported performance metrics represent single-run point estimates without confidence intervals or statistical significance testing. The comparison between YOLO models is therefore based on numerical differences that may not reflect true statistical separation, especially given the close mAP and recall values observed across models. Without repeated trials, variance reporting, or hypothesis testing such as paired t-tests or Wilcoxon signed-rank tests, the conclusion regarding model superiority remains provisional rather than statistically validated. Future work should include multi-run evaluations, confidence-bound reporting, and formal statistical comparison to ensure that observed performance differences are robust, reproducible, and not attributable to stochastic variation in the training process.

8. Declarations

8.1. Author Contributions

Conceptualization: W.S.N., J.A., T.K., K.S.N., K.S.N., and P.N.; Methodology: W.S.N., J.A., T.K., K.S.N., K.S.N., and P.N.; Software: W.S.N., J.A., T.K., K.S.N., K.S.N., and P.N.; Validation: W.S.N., J.A., T.K., K.S.N., K.S.N., and P.N.; Formal Analysis: W.S.N., J.A., T.K., K.S.N., K.S.N., and P.N.; Investigation: W.S.N., J.A., T.K., K.S.N., K.S.N., and P.N.; Resources: W.S.N., J.A., T.K., K.S.N., K.S.N., and P.N.; Data Curation: W.S.N., J.A., T.K., K.S.N., K.S.N., and P.N.; Writing Original Draft Preparation: W.S.N., J.A., T.K., K.S.N., K.S.N., and P.N.; Writing Review and Editing: W.S.N., J.A., T.K., K.S.N., K.S.N., and P.N.; Visualization: W.S.N., J.A., T.K., K.S.N., K.S.N., and P.N.; All authors have read and agreed to the published version of the manuscript.

8.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

8.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

8.4. Institutional Review Board Statement

Not applicable.

8.5. Informed Consent Statement

Not applicable.

8.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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