

Embedded Intelligent Microscopy System for Identification and Counting of Microscopic Marine Organisms

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Abstract- The design, implementation, and assessment of an Embedded Intelligent Microscopy System (EIMS) for the automatic identification and counting of tiny sea animals (phytoplankton and zooplankton) are presented in this study. A low-cost optical microscope, on board image capturing, real-time preprocessing, and a lightweight convolutional neural network for object recognition and classification implemented on an embedded platform are all integrated into the system. We outline the model architecture and optimization for embedded inference, evaluation metrics, training dataset preparation, imaging pipeline, and hardware design. While operating at 7-12 frames per second on the target embedded platform, results on a mixed dataset of typical coastal microplankton show classification accuracy of 91.7% (macro-averaged F1 = 0.90) and counting error (mean absolute percentage error) of 6.8% on held-out test samples. We talk about future work toward in-situ deployment on autonomous sampling devices, ecological utility, and system limits.

Keywords- Embedded microscopy, marine microorganisms, plankton identification, lightweight CNN, automated counting, in-situ monitoring.

I. INTRODUCTION

Phytoplankton and tiny zooplankton are microscopic marine animals that constitute the foundation of aquatic food webs and are important markers of carbon cycling, hazardous algal blooms, and ecosystem health. Manual sampling and tedious microscopy by qualified taxonomists are necessary for traditional monitoring, which is slow, expensive, and challenging to scale. Large-scale spatial temporal research, near real-time counts and faster monitoring

are all made possible by automated systems that integrate optical imaging with machine learning (ML). An Embedded Intelligent Microscopy System (EIMS) for the identification and measurement of common microscopic marine creatures is presented in this research. Our objectives were to:

- (1) Create a low-cost, reliable hardware and imaging pipeline for field or shipboard use.
- (2) Create an effective image-processing and machine learning pipeline that functions well under real-world imaging variability.
- (3) Optimize and implement the model on an embedded compute board to enable real-time, in-situ analysis.

II. RELATED WORK

For twenty years, research on automated plankton imaging and categorization has been ongoing. Methods include deep learning techniques that use convolutional neural networks (CNNs) to directly learn discriminative features from pictures, as well as traditional feature-based categorization (shape, texture, and morphology). Flow cytometry-based imagers, high-throughput imaging flow cytobots, and benchtop imaging systems combined with deep learning algorithms are examples of earlier systems. Current advancements focus on the usage of U-Net and object-detection networks for segmentation and counting, as well as implementation on low-power systems for in-situ monitoring.

III. SYSYTEM ARCHITECTURE

Hardware Components

- Optical System: 10×–40× objective lenses with condenser illumination.
- Camera: Global-shutter CMOS sensor (≥ 5 MP).
- Embedded Platform: ARM-based SBC with NPU/TPU or NVIDIA Jetson-class hardware.
- Sample Chamber: Flow-cell structure to minimize organism overlap.

Software Pipeline

- Image acquisition using autofocus routines.
- Preprocessing: noise reduction, flat-field correction, and contrast enhancement.
- Segmentation using adaptive thresholding and morphological filtering.
- Classification via a MobileNetV3-based lightweight CNN.
- Postprocessing for count stabilization.

IV. DATASET

Robust categorization of marine organisms requires a representative and diversified dataset. The species gathered from coastal water samples using typical plankton nets (20–60 μm mesh size) are included in the dataset utilized in this investigation. Calibrated microscopy equipment were used to image samples while they were briefly preserved. To improve class imbalance and increase taxonomic diversity, publicly accessible microplankton datasets were also used.

Bounding boxes and class labels were used by skilled observers to manually annotate images. To avoid incorrect classifications, ambiguous samples, overlapping species, and damaged specimens were placed in the "unknown" category. Better model generalization is ensured by this meticulous curation.

12,400 tagged samples from 14 different microplankton types are included in the collection. To increase robustness, data augmentation was used.

V. MODEL DESIGN AND OPTIMIZATION

A lightweight CNN architecture designed for embedded system deployment is used in the suggested approach. A MobileNetV3 backbone is used for

feature extraction because it strikes a compromise between computational efficiency and accuracy. An SSD-like multi-scale prediction head is used for detection.

To make real-time inference even more possible:

- Quantization-aware training minimizes accuracy loss while increasing speed and reducing model size.
- Redundant filters are eliminated by structured pruning.
- Throughput is maximized by hardware-accelerated inference engines like ONNX Runtime and TensorRT. Together, these improvements lower latency and power consumption, which qualifies the system for use in distant sensing applications.

SSD-style detection was employed with a MobileNetV3 backbone. Quantization aware training, pruning and TensorRT acceleration are examples of embedded optimization approaches.

VI. TRANNING ANDEVALUATION

Adam optimizer with cosine LR scheduling was utilized for training. Precision, recall, F1 score, mAP, MAE, and MAPE were among the metrics.

VII. RESULTS

Three main factors are evaluated: embedded inference efficiency, counting performance, and classification accuracy. The improved training process and expanded dataset improved the model's resilience to changes in light, orientation, and morphology. While comparable species showed predicted overlap, confusion matrix analysis revealed little misinterpretation among visually dissimilar taxa.

Classification

The model achieved 91% precision, 90% recall, and 0.90 F1-score.

Counting

6.8% was the average absolute percentage inaccuracy.

Embedded Performance

With an average power usage of 7.4 W, Real-time inference at 7-12 FPS was accomplished.

VIII. DISCUSSION

The technology offers an affordable way to monitor plankton. Sensitivity to picture quality and challenges managing highly overlapping organisms are among the limitations.

IX. CONCLUSION

An Embedded Intelligent Microscopy System was created to identify and count marine microorganisms. The system performs effectively and with excellent precision, making it appropriate for real-time field applications.

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