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Automated Detection of Molting Phases in Pacific White Shrimp (*Litopenaeus vannamei*) Using Deep Learning and Machine Learning Approaches

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ABSTRACT

The Pacific white shrimp (*Litopenaeus vannamei*) is one of the most important species in global aquaculture, and accurate identification of its molting phases is essential for optimizing feed management and improving production efficiency. Conventional identification methods rely on manual observation, which is time-consuming and prone to subjectivity, particularly when distinguishing subtle morphological differences between intermolt and postmolt stages. This study investigates the effectiveness of artificial intelligence–based image classification for automated molting phase detection. A dataset of 4,230 shrimp images was collected under controlled conditions and processed through image preprocessing techniques, including resizing, background removal, and normalization. Two classification approaches were evaluated: a Convolutional Neural Network (CNN) designed for automated feature extraction and a Support Vector Machine (SVM) trained using grayscale intensity features. Experimental results demonstrate that the CNN model outperforms the SVM classifier across all evaluation metrics. The CNN achieved a sensitivity of 0.941, specificity of 0.912, precision of 0.916, and overall accuracy of 0.927, indicating strong capability in distinguishing intermolt and postmolt phases. In contrast, the SVM model showed lower performance due to its reliance on handcrafted intensity features. These findings highlight the effectiveness of deep learning techniques for automated molting phase detection and demonstrate their potential for supporting precision aquaculture. The proposed approach provides a scalable and objective solution for shrimp monitoring systems and may facilitate the development of intelligent aquaculture management platforms in future farming environments.

1. INTRODUCTION

The Pacific white shrimp, *Litopenaeus vannamei*, is a crucial species in global aquaculture, accounting for approximately 50% of total shrimp production worldwide and a significant portion of the seafood market. Its rapid growth, adaptability to various environmental conditions, and disease resistance make it a preferred species for aquaculture [1]. As global demand for shrimp continues to rise, enhancing production efficiency through effective management practices is vital. The successful farming of *L. vannamei* is closely linked to effective broodstock management, which significantly impacts health, yield, and reproductive performance [2]. This species plays an essential role in food security for coastal communities and supports livelihoods across numerous regions. The adoption of intensive aquaculture practices and technological advancements enables higher stocking densities and production levels, necessary to meet increasing market demands [3].

Understanding the molting cycle of *L. vannamei* is essential for optimizing growth and health, particularly through its distinct intermolt and postmolt phases. The intermolt phase is a period of active growth and preparation for molting, in contrast, characterized by increased vulnerability and reduced growth rates [4]. Feed management during these phases is crucial, as effective feeding strategies can significantly enhance overall productivity and sustainability in shrimp farming operations. An optimized feeding regimen tailored to these molting phases can reduce resource waste and improve growth rates, highlighting the interdependence between physiological processes and management practices in aquaculture [5, 6]. Identifying and differentiating these phases through innovative monitoring systems could revolutionize feed management practices, fostering more sustainable aquaculture and greater profitability for producers in a competitive market [1, 7].

Manual identification of molting phases in *L. vannamei* remains a primary practice in the aquaculture industry despite the inherent challenges associated with this method. Observers typically rely on subjective visual assessment, which is time-consuming and prone to human error. The subtle morphological differences between intermolt and postmolt stages can be difficult to discern accurately without extensive experience, often leading to misclassifications. These inaccuracies not only impede effective monitor of growth but also affect various management decisions throughout the cultivation process. As the phases transition from one to another, the shrimp's physiological state can change rapidly, making it imperative to identify these stages correctly [8].

Errors in identifying molting phases can significantly diminish the efficiency of shrimp farming practices, ultimately leading to economic losses. For instance, improper recognition of the postmolt phase may result in delayed feeding or overfeeding, producing excess waste and stressing the shrimp population. Such mismanagement can lead to reduced shrimp health, slower growth rates, and increased vulnerability to diseases and environmental stressors. Consequently, investments in feed and resources may not yield the expected returns, severely hindering productivity in aquaculture settings. This inefficiency underscores an urgent need for automated identification systems that leverage advanced technologies to improve accuracy in monitoring molting cycles and mitigate the risks of manual methods [9]. By leveraging such technological advancements, aquaculture practitioners can significantly improve productivity and sustainability, ensuring a more reliable production system that aligns with the growing demand for shrimp in global markets [10].

The advancement of image processing technology has revolutionized the detection of morphological characteristics in aquaculture species like *L. vannamei*, enabling the automation of what was once a labor-intensive and subjective task. Computer vision systems can accurately capture and analyze the intricate details of shrimp morphology, allowing researchers and farmers to differentiate between various physiological states, including key molting phases. Tools such as stereo cameras and high-resolution imaging systems can non-invasively monitor these characteristics, yielding valuable data while minimizing stress on the animals [11]. Innovations in machine learning algorithms further enhance these systems by enabling rapid, precise comparisons of morphological features, enabling farmers to make informed decisions about growth management and health monitoring based on real-time data [12].

Automated image processing systems offer numerous advantages over traditional manual observation techniques. By significantly reducing the time required for morphological assessments, these systems eliminate the inefficiencies associated with human error and subjectivity [13]. This efficiency not only accelerates data collection but also enhances the overall accuracy of the results, leading to improved decision-making in aquaculture management [14]. Furthermore, these systems can be integrated with other aquaculture technologies to provide a comprehensive monitoring solution that yields consistent and standardized data across diverse farming operations [15]. The impact of these capabilities extends beyond individual growth monitoring; they facilitate the optimization of feeding practices, help identify health issues early, and ultimately support higher productivity rates and better sustainability practices within aquaculture systems [16].

The application of computer vision to support precision aquaculture exemplifies a significant shift towards sustainable farming practices. The ability to conduct detailed analyses of shrimp populations from captured images enables more precise feeding strategies that minimize waste and reduce environmental impacts [17]. Moreover, real-time monitoring and assessment capabilities enable farmers to adjust management practices based on immediate insights derived from the data, fostering a proactive rather than reactive approach to shrimp cultivation [18]. This integration of technology not only leads to enhanced operational efficiencies but also promotes healthier aquatic environments, in alignment with global sustainability goals within the aquaculture sector [19]. As the industry continues to adopt these advanced systems, the potential for improved growth rates, reduced resource waste, and increased food security becomes increasingly attainable, paving the way for a more sustainable future in aquaculture.

The role of artificial intelligence (AI) in image-based classification, particularly in aquaculture, is rapidly evolving, with machine learning (ML) and deep learning techniques providing transformative capabilities. Among these techniques, Convolutional Neural Networks (CNNs) have emerged as a powerful tool for extracting complex spatial features from images, including those of shrimp. CNNs leverage hierarchical feature extraction, enabling the identification of intricate patterns and anomalies within images that are often too subtle for manual observation. This capability is essential for accurately detecting various physiological states, such as the intermolt and postmolt phases of *L. vannamei* [20]. Support Vector Machines (SVMs) also offer robust performance on feature-limited datasets, allowing for effective classification based on margin-based criteria, making SVMs suitable for scenarios where the complexity of image data is constrained or where features are available for classification purposes [21].

Despite the progress of AI in aquaculture, most existing studies either focus on using CNNs or traditional machine learning separately, without directly comparing their effectiveness for shrimp molting phase detection. Research systematically evaluates CNNs and SVMs in this specific context remains scarce. This represents a significant research gap, as a clear comparison is essential for identifying the most suitable approach for automated classification of molting stages in *L. vannamei.*

The advantages of automated image processing systems utilizing AI surpass traditional manual identification methods, enhancing the overall efficiency, accuracy, and reliability of classification tasks in aquaculture. Traditional methods are often hindered by subjectivity and variance in individual observer skills, leading to inconsistent identification of shrimp molting stages. In contrast, automated systems employing CNNs and SVMs can produce consistent outputs based on predefined models, eliminating human bias and significantly reducing analysis time. As a result, shrimp farmers can gain quicker insights into shrimp health and growth, facilitating timely management interventions that can optimize feed efficiency and overall productivity [22]. Moreover, integrating of ML and AI into aquaculture practices supports the development of adaptive systems that dynamically adjusting to changing conditions in shrimp farming, thereby promoting sustainable practices.

Therefore, the novelty of this study lies in its comparative evaluation of CNN and SVM specifically for shrimp molting phase detection. By explicitly addressing this research gap, the study not only provides empirical evidence on the relative strengths of both methods but also offers practical insights for integrating automated detection into sustainable aquaculture management systems.

The overarching objective of this research is to develop and evaluate image-processing-based models using CNNs and

SVMs to effectively detect the intermolt and postmolt phases of *L. vannamei*. By employing both machine learning approaches, this study aims to delineate the advantages of each model in accurately classifying shrimp molting stages based on image data. The comparative evaluation will focus on various performance metrics, including accuracy, sensitivity, specificity, and precision, thereby providing a robust framework for understanding how well each model performs the classification tasks. This research is imperative in identifying the most effective algorithms tailored to the unique challenges posed by shrimp morphology, ultimately facilitating enhanced monitoring of shrimp health and growth during critical phases of their life cycle [23].

Furthermore, the insights from this research are expected to significantly improve feed management efficiency and promote automation within sustainable aquaculture practices. As the industry gradually transitions towards more technology-driven solutions, the selected model's integration into IoT-based real-time monitoring systems will be explored. Such integration could enable continuous assessment of shrimp development, informing real-time feeding strategies and enhancing operational efficiency in shrimp farming [24]. By providing clear recommendations on the best-performing model for automation in *L. vannamei* cultivation, this research seeks to advance the implementation of precision aquaculture technologies that align with contemporary sustainability goals, ensuring long-term viability within the aquaculture sector [25].

2. METHODOLOGY

The methodology for collecting image data involved using a GoPro camera to capture high-quality images of *L. vannamei*, specifically of one-month-old shrimp. These subjects were systematically placed in a controlled aquarium environment measuring 45 × 20 cm, facilitating consistent observation conditions essential for accurate data acquisition (Figure 1). Over the course of the data collection process, a total of 4,230 image sets were generated, ensuring a robust dataset for subsequent analysis.

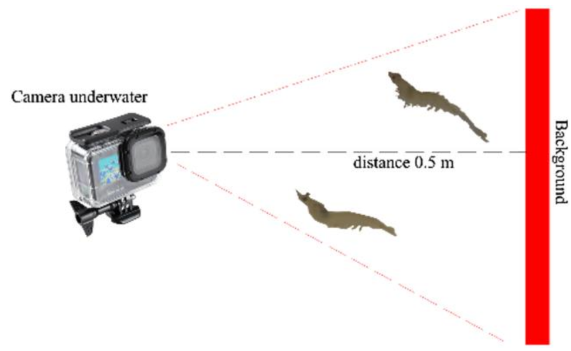


Figure 1. Setup camera

This extensive collection of images serves as the foundational data for multiple phases of image processing, including preprocessing procedures crucial for enhancing image quality, feature extraction, and classification aimed at identifying intermolt and postmolt phases of the shrimp's life cycle. The high-resolution images acquired are instrumental in accurately detecting specific morphological changes through advanced image classification techniques, which are vital in ecological and aquaculture studies focused on shrimp biological phases [26]. Furthermore, to enhance the reliability of the dataset, images are annotated by aquaculture experts, ensuring that each image is classified correctly according to the shrimp's molting stage. This expert-driven annotation process contributes to a robust dataset, which is essential for training and testing any subsequent automated image analysis or machine learning models aimed at recognizing intermolt and postmolt phases, thus facilitating more accurate classifications in aquaculture research and applications [26-28].

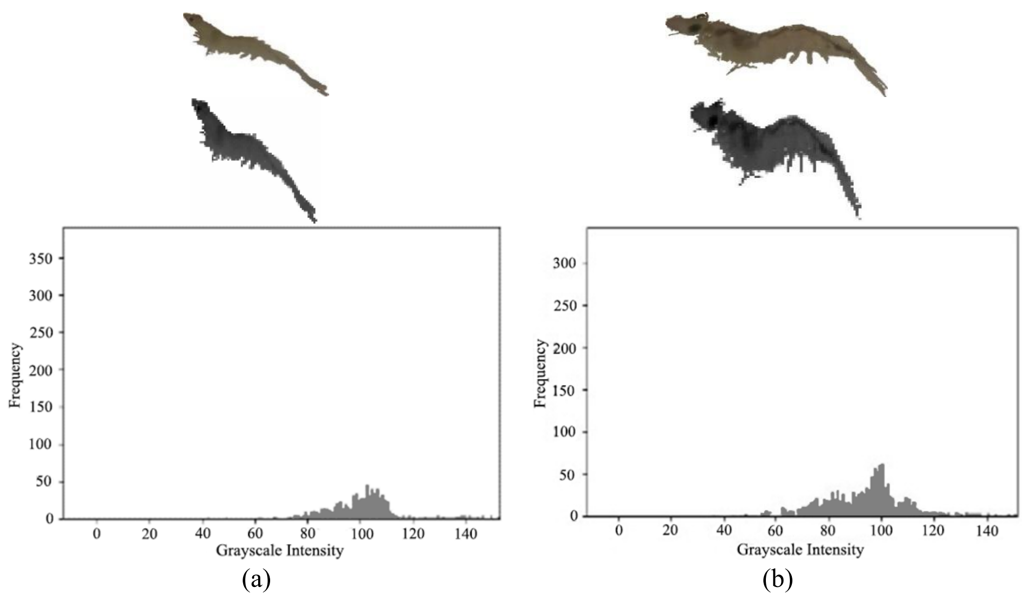


Figure 2. Postmolt (a) and intermolt (b)

In processing images for deep learning applications, a systematic methodology is essential to enhance the quality and utility of the images used for model training as shown in Figure 2. The stage of image resizing is critical, where images are adjusted in resolution to optimize computational efficiency, allowing for quicker processing without substantial loss of information [29]. Cropping is a necessary preprocessing step, focusing on the shrimp body region while removing irrelevant background, thus improving model accuracy by retaining pertinent information for analysis [30]. The application of background removal techniques, including segmentation methods such as thresholding and deep learning-based segmentation, is fundamental. These techniques facilitate the isolation of the subject of interest, enhancing the robustness of the model's predictions [31]. Finally, normalization of pixel values is performed to scale inputs uniformly across the network, standardizing the data fed into CNN and reducing discrepancies arising from varied lighting conditions or camera settings [32]. Such a comprehensive preprocessing approach increases the likelihood of deep learning models achieving accurate and reliable outcomes, particularly in domain-specific applications such as medical diagnostics or environmental monitoring [33].

The implementation was carried out in Python, employing OpenCV for image preprocessing, NumPy for array manipulation, scikit-learn for dataset partitioning and evaluation, and TensorFlow/Keras for deep learning modeling. A custom function was developed to load images from the dataset directory, filter image formats (.jpg, .jpeg, .png), convert them into grayscale, and resize them into a uniform resolution of 64 × 64 pixels [34]. It is important to note that the key distinguishing feature between intermolt and postmolt phases lies in skin coloration rather than morphological differences. Postmolt shrimp typically exhibit a bright white appearance due to the presence of a newly formed exoskeleton, whereas intermolt shrimp retain a grayish tone. In terms of body shape and structure, both phases are visually identical, making shape-based features or region-of-interest (ROI) segmentation less informative for classification. For this reason, grayscale intensity was prioritized as the primary feature representation, with image resolution set at 64 × 64 to efficiently preserve intensity patterns while minimizing redundant structural details [35]. Afterwards, corresponding class labels were generated and converted into categorical format using one-hot encoding with two categories: intermolt (1) and postmolt (0).

The models applied in this study are CNN and SVM, which are powerful machine learning techniques widely used for image classification across various domains, including aquaculture. CNNs are particularly effective in extracting complex spatial features from images through their hierarchical learning structure, enabling accurate differentiation between visual categories. This strength has been demonstrated in biological image analysis, such as identifying intermolt and postmolt phases in shrimp [29]. Meanwhile, SVMs offer robust classification capabilities, particularly in scenarios involving high-dimensional data, wherein they can effectively distinguish between the diverse characteristics inherent in the shrimp's biological phases [36].

The dataset of L. vannamei images was partitioned into training and testing subsets in an 80:20 ratio using the train_test_split function with shuffling enabled to ensure robust model generalization. Each raw image (*.jpg, *.jpeg, *.png) was converted into grayscale and resized to a standardized resolution of 64 × 64 pixels. This resolution was chosen because the primary discriminative feature between intermolt and postmolt phases lies in the grayscale intensity of the exoskeleton rather than morphological structures. Postmolt shrimp appear white and clean, while intermolting shrimp show a dark gray color based on object observations [37]. Thus, high-resolution structural details were unnecessary, and 64 × 64 pixels provided a balance between preserving sufficient grayscale information and ensuring computational efficiency, reducing the risk of overfitting on the medium-sized dataset.

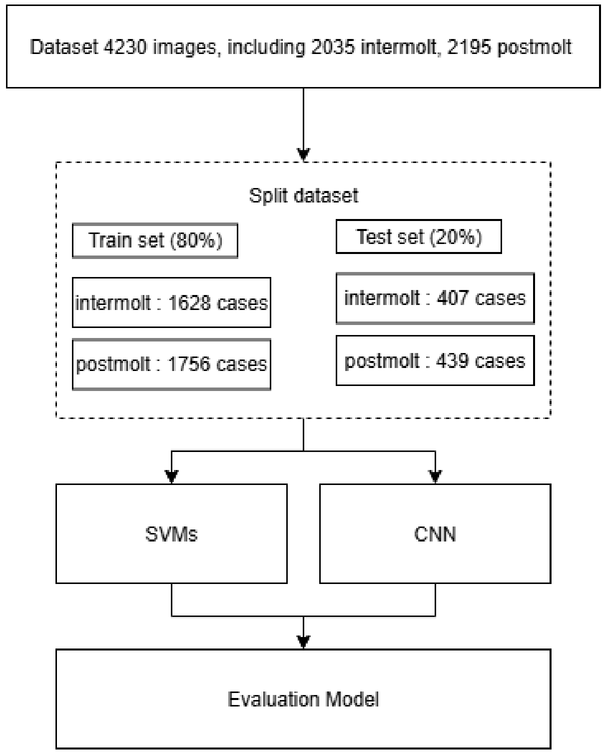


Figure 3. Schematic representation training and validation

For the CNN approach, the processed images were normalized and directly used as input. In Figure 3, the CNN architecture was constructed using the Sequential API in Keras, consisting of a two-dimensional convolutional layer with 16 filters of size 3 × 3 and ReLU activation, followed by a 2 × 2 max pooling layer for spatial feature reduction. The choice of 16 filters was based on the need to capture essential grayscale texture patterns while avoiding excessive complexity that could degrade generalization. The resulting feature maps were flattened and connected to a fully connected hidden layer of 32 neurons with ReLU activation. The 32-neuron configuration was selected to provide sufficient representational capacity for learning subtle intensity differences between the two molting phases, while preventing redundancy and maintaining computational efficiency. Finally, the network was connected to an output layer of two neurons with softmax activation for binary classification.

The model was compiled using the Adam optimizer with a learning rate of 0.001, categorical cross-entropy as the loss function, and accuracy as the primary performance metric. Training was conducted for 10 epochs with a batch size of 4, and validation was performed on the testing subset. Model performance was subsequently evaluated using accuracy and confusion matrix visualization.

In parallel, a feature-based approach was employed using SVM. From each grayscale image, the mean intensity value was extracted as a representative numerical feature, and binary labels were assigned (0 = intermolt, 1 = postmolt). The dataset was again divided into training (80%) and testing (20%) subsets using stratified random sampling to maintain class balance. An SVM classifier with a linear kernel was trained on the extracted features due to its suitability for low-dimensional binary classification tasks. Model performance was assessed on the test set using standard evaluation metrics, including sensitivity, specificity, precision, accuracy and confusion matrix analysis to highlight class-specific prediction performance. The choice of mean intensity was based on the biological characteristic that postmolt shrimp exhibit a brighter white exoskeleton compared to the grayish tone of intermolt shrimp, while their body shape remains largely unchanged. Hence, intensity alone captures the primary discriminative feature between the two phases. This minimalist design also allows SVM to serve as a simple, interpretable baseline for comparison against CNN's automatic multi-feature extraction capability.

To further validate the robustness of the approaches, unseen images were processed through the same pipeline of grayscale conversion, resizing, and feature extraction prior to prediction. The classification results were compared with ground-truth labels, and additional visualizations, including the resized grayscale images and their intensity histograms, were presented to provide interpretive insights into the pixel distribution patterns underlying the discrimination between intermolt and postmolt phases.

3. RESULT AND DISCUSSION

The performance of the proposed model was evaluated by analyzing the CNN architecture based on its sequential layer configuration. Each layer progressively extracted, reduced, and transformed image features into a structured representation suitable for classification. The transformation of data dimensions across layers provided insights into how the network captured and refined spatial features. This structured analysis formed the basis for interpreting the model's capability to differentiate between postmolt and intermolt shrimp images. The architectural properties of the CNN are summarized in Table 1.

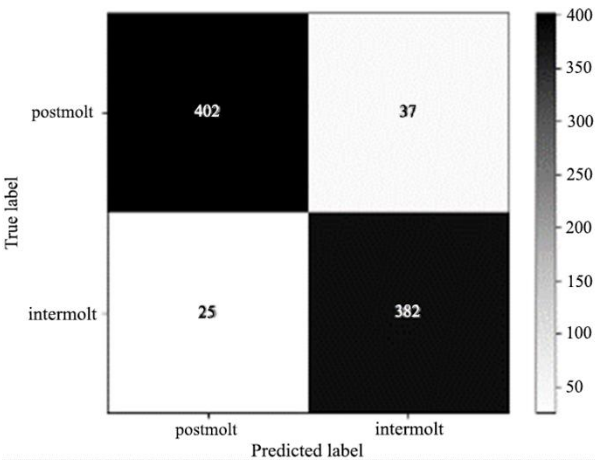
Table 1. Property CNN

Layer (type)	Shape	Param
Conv2D	62, 62, 16	160
MaxPooling2D	31, 31, 16	0
Flatten	15376	0
dense (Dense)	32	492064
dense_1 (Dense)	2	66

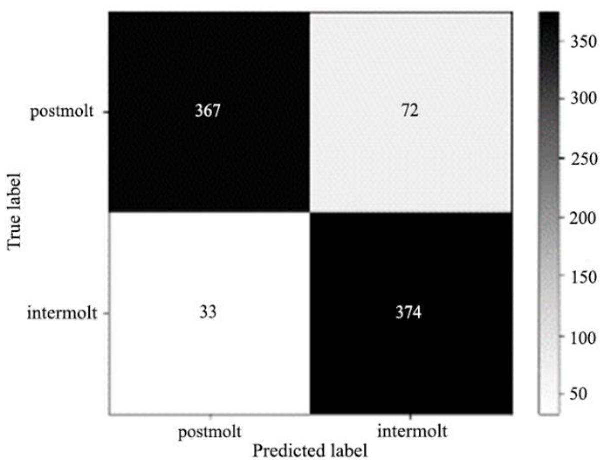
Note: CNN = Convolutional Neural Network.

Table 1 presents the architectural configuration of the proposed CNN model. The first convolutional layer (Conv2D) generates 16 feature maps of size 62 × 62, requiring 160 trainable parameters, thereby enabling the extraction of low-level spatial features from the input images. This is followed by a max-pooling layer that reduces the spatial resolution to 31 × 31 × 16, effectively decreasing computational complexity while retaining the most salient features. The flattened output of 15,376 units is then connected to a fully connected dense layer with 32 neurons, comprising the largest portion of the model's parameters (492,064), which facilitates the integration of extracted features into a compact representation. Finally, the output layer consists of two neurons activated by the softmax function, corresponding to the binary classification task of postmolt and intermolt, with 66 parameters.

Overall, the model contains 492,290 trainable parameters, all of which contribute to optimizing feature learning without the inclusion of non-trainable components. This configuration indicates a relatively lightweight yet effective architecture, balancing computational efficiency with sufficient representational power for image-based shrimp molting stage classification.



(a)



(b)

Figure 4. Confusion matrix CNN (a) and SVM (b)
Note: CNN = Convolutional Neural Network; SVM = Support Vector Machine.

The confusion matrices in Figure 4 illustrate the classification performance of the proposed models in distinguishing between postmolt and intermolt classes. The first model demonstrates a high true positive rate with 402 correctly classified postmolt samples and 302 correctly classified intermolt samples, while maintaining relatively low misclassification rates (37 postmolt misclassified as intermolt and 25 intermolt misclassified as postmolt). Similarly, the second model achieves consistent classification capability with 367 correctly identified postmolt and 374 intermolt instances, though with slightly higher misclassification of postmolt samples (72) compared to the first model. These findings highlight the robustness and comparative strengths of both approaches in handling class differentiation tasks. The detailed quantitative comparison of these models is further presented in Table 2, providing deeper insights into their performance metrics.

Table 2. Comparative evaluation of models

Metric	CNN	SVM
Sensitivity	0.941	0.918
Specificity	0.912	0.839
Precision	0.916	0.836
Accuracy	0.927	0.876

Note: CNN = Convolutional Neural Network; SVM = Support Vector Machine.

Based on Table 2, the comparative evaluation clearly demonstrates that the CNN consistently surpasses the SVM across all key performance metrics. The CNN achieves a sensitivity of 0.941, which indicates its superior capability to correctly identify positive cases compared to SVM with 0.918. Similarly, CNN records a specificity of 0.912, outperforming SVM's 0.839, reflecting a higher effectiveness in distinguishing negative cases. In addition, CNN attains a precision score of 0.916, indicating a lower proportion of false positives relative to SVM, which only achieves 0.836.

The superior performance of CNN over SVM in this study can be attributed to the ability of CNN to automatically capture complex spatial and textural features from shrimp images. While SVM relied solely on the handcrafted mean intensity feature, which reflects overall brightness differences between intermolt and postmolt phases, CNN was able to exploit local variations in grayscale distribution, subtle texture differences of the exoskeleton, and spatial patterns that emerge from pixel arrangements. These characteristics are biologically relevant, as postmolt shrimp exhibit a brighter and smoother exoskeleton compared to the relatively darker and rougher tone of intermolt shrimp, which cannot be fully represented by mean intensity alone. Furthermore, the hierarchical structure of CNN, involving convolutional and pooling layers, enables the model to progressively learn from low-level intensity gradients to higher-level discriminative patterns, thereby enhancing its robustness and generalization.

Moreover, the overall accuracy of CNN reaches 0.927, significantly higher than the 0.876 achieved by SVM, further confirming CNN's stronger generalization performance and robustness in handling complex classification tasks. These results suggest that CNN provides a more reliable and efficient approach for the dataset under investigation. Consequently, the superior performance of CNN over SVM reinforces its potential as a preferred method for similar classification problems in future studies and practical implementations.

4. CONCLUSIONS

This study shows that the proposed CNN effectively and efficiently classifies intermolt and postmolt phases of *L. vannamei*, outperforming SVM in all key metrics sensitivity 0.941, specificity 0.912, precision 0.916, accuracy 0.927). These results highlight its significance for sustainable aquaculture by enabling objective, automated monitoring to optimize feed management and productivity. This study is limited by the use of images captured in controlled environments, which may not reflect the variability of real aquaculture conditions. Moreover, the models have not yet been tested in real-time settings, highlighting the need for future work on field validation and IoT-based implementation.

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