Visual dataset of shrimp for support in classification and comparative studies using convolutional neural networks (CNNs)

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Submitted: January 05, 2026 DOI: 10.14295/bjs.v5i5.870

Accepted: April 16, 2026 URL: https://doi.org/10.14295/bjs.v5i5.870

Published: April 30, 2026

Abstract

This study presents a dataset for the construction of a neural network from images of refrigerated shrimp. The images were collected at different times, during which the shrimp went from capture to the final degradation stages. After collection, the images were organized chronologically and subjected to a selection process. The Python program was applied for lighting and blur corrections, preparing the data for the modeling phase. The neural network was developed in the Keras program, with diversified learning methods to form a model capable of evaluating shrimp quality in different periods. Therefore, this study resulted in a dataset that is essential for training the CNN, and as the image quality and the processing methodology adopted were crucial to identify the defects and colorimetric modifications of the shrimp, offering an accuracy above 95%, it can therefore be considered a suitable and innovative tool for quality control in the shrimp farming industry.

Keywords: food computing, image, seafood, convolutional neural networks.

Conjunto de dados visuais de camarões para apoio à classificação e estudos comparativos utilizando redes neurais convolucionais (CNNs)

Resumo

Este estudo apresenta um conjunto de dados destinado à construção de uma rede neural a partir de imagens de camarões refrigerados. As imagens foram coletadas em diferentes momentos, nos quais os camarões evoluíram desde a captura até os estágios finais de degradação. Após a coleta, as imagens foram organizadas cronologicamente e submetidas a um processo de seleção. Um programa em Python foi aplicado para correções de iluminação e desfoque, preparando os dados para a fase de modelagem. A rede neural foi desenvolvida no ambiente Keras, utilizando métodos de aprendizagem diversificados, com o objetivo de formar um modelo capaz de avaliar a qualidade dos camarões em diferentes períodos. Dessa forma, o estudo resultou em um conjunto de dados essencial para o treinamento da CNN. Considerando que a qualidade das imagens e a metodologia de processamento adotada foram fundamentais para a identificação de defeitos e modificações colorimétricas dos camarões, alcançando uma acurácia superior a 95%, o método pode ser considerado uma ferramenta adequada e inovadora para o controle de qualidade na indústria da carcinicultura.

Palavras-chave: computação aplicada a alimentos, imagem, frutos do mar, redes neurais convolucionais.

1. Introduction

Litopenaeus vannamei is one of the shrimp species cultivated and commercialized in many countries (Zhang et al., 2021). The Northeast region in Brazil is home to significant shrimp farming due to its edaphoclimatic conditions, which are favorable to the adaptation of this species, corresponding to 98% of the country's total production (Lacerda et al., 2021). In parallel, shrimp *L. vannamei* is a highly perishable crustacean, resulting in a short shelf life, making it more susceptible to biochemical reactions and microbiological changes. Spoilage is mainly caused by bacteria, chemical reactions, and intrinsic enzymes, resulting in loss of sensory quality. These changes occur due to handling, processing, and natural microbiota, accelerating quality changes in refrigerated products (Kimbuathong et al., 2020).

Due to characteristic changes throughout its degradation, image analysis can be applied to segment, classify, and detect defects such as stains, coloring, wrinkling, among other apparent factors that enable rapid, precise, and reliable distinction, without destroying the product, reducing human effort, and minimizing contamination risk. In turn, segmentation algorithms can identify and quantify subtle color variations, enabling automatic classification of foods based on their visual characteristics, in addition to being a crucial technique that allows extracting relevant features, such as shape and texture, which are fundamental for assessing food quality (Junior; da Silva, 2023). In this sense, creating a dataset containing images of refrigerated shrimp at different deterioration stages and analysis variations can help researchers, students, and professionals in understanding the degradation process of this food.

Convolutional Neural Networks (CNNs) are a specific type of deep neural network designed to process grid-structured data, such as images and time series. They apply convolutional layers, which enable detecting and analyzing local features in the input data, such as color, edges, textures, and patterns, which are later used to classify each pixel in the image and perform segmentation. According to Napoli et al. (2020), a neural network is "a learning system which uses layers of artificial neurons to process data in regions with several pixels and learn complex patterns", being fundamental for advances in areas such as computer vision and natural language processing. Complementing this view, Zhang et al. (2020) describe deep neural networks as "structures composed of multiple layers of neurons which enable modeling highly complex and non-linear data", demonstrating superior performance in tasks such as image recognition and machine translation.

Unlike manual feature extraction methods, CNNs offer a scalable approach to image classification and object recognition tasks based on linear algebra principles, such as matrix multiplication, to identify patterns within an image. Goodfellow et al. (2016) highlight that training these networks has been crucial for advances in areas such as computer vision and speech recognition.

In this sense, this study aimed to develop a dataset for later application in training and construction of a CNN with digital images of refrigerated shrimp, with the aim that the AI establishes identification of both heterogeneous and homogeneous patterns, and that it serves as a basis for later application in innovative quality control tools in the shrimp farming industry.

2. Materials and Methods

2.1 Materials

The whole shrimp was purchased commercially from a farm located in Acaraú, CE, Brazil. Immediately after harvesting, they were slaughtered by hypothermia, with ice water below 0 ± 1 ºC. They were transported immersed in blocks of ice, in thermal boxes, and kept under refrigeration (0 ± 1 ºC) to the Meat and Fish Processing Plant (PPCP) of the Federal Institute of Ceará - Sobral campus to be evaluated and obtain the images. The sample consisted of 150 shrimp units selected for training and testing, considering the species and state of the shrimp, during the periods of 0, 3, and 6 days.

2.2 Data collection

A Galaxy S20 FE smartphone was used to capture the images, equipped with a 6.5-inch display, 128GB storage, a 12MP+12MP+8MP triple camera setup, and a 2.8GHz Octa-Core processor. All the refrigerated shrimp samples were carefully positioned inside a support box during this phase of the experiment (Figure 1).

Figure1. Images of the support box used to obtain sample images. Source: Authors, 2025.

The digital images were obtained by positioning the cell phone on the top of the support box parallel to the base, and then starting the collection, which occurred in two ways: the images were initially taken in triplicate to ensure excellent focus (Figure 2), but throughout the process it was necessary to slightly enlarge the size of the samples to improve their visualization without applying zoom so as not to distort the images; thus arriving at the second method, which consisted of using a raised rotating base (Figure 3) which combined with the smartphone's "Single Take" capture function, which enables taking 100 photos over 5 seconds of each distinct position of the shrimp. In turn, only 6 images of the set are separated (Figure 4) through a contrast analysis and without proximity in position.

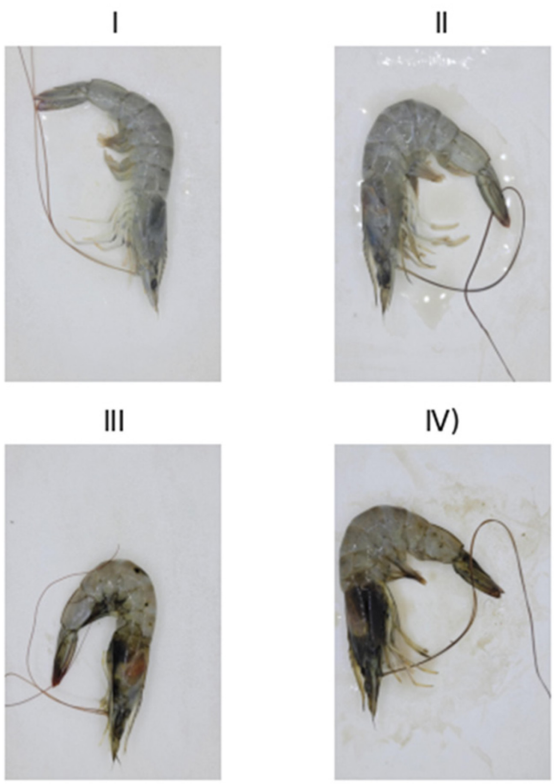

Figure 2. The photographic image of shrimp inside the support box with different decomposition states is very clear. I) Day it was caught; II) 3 days after catching; III) 6 days after catching; IV) More than 9 days after catching. Source: Authors, 2025.

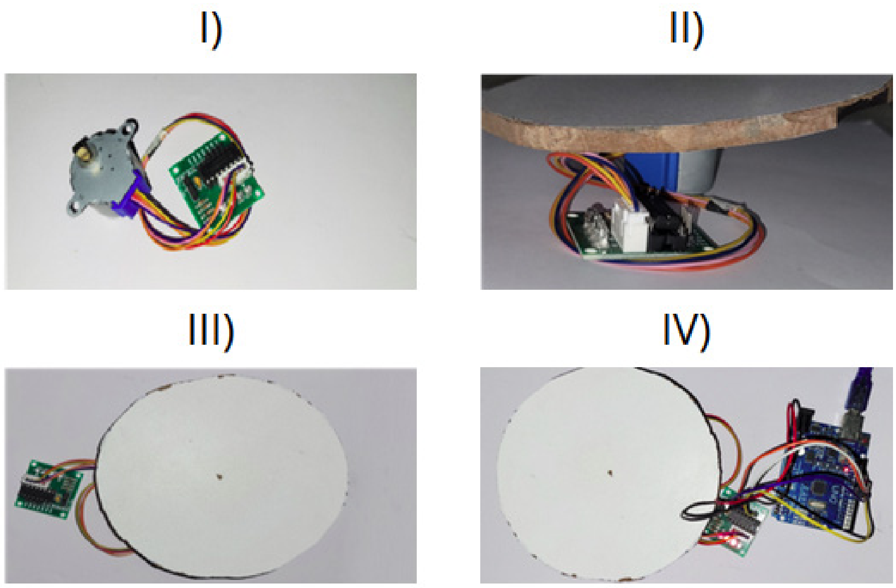

Figure 3. Photographic image of the components of the turntable. I) motor with module; II) motor with the turntable; III) top photographic image of the turntable; IV) complete circuit of the turntable. Source: Authors, 2025.

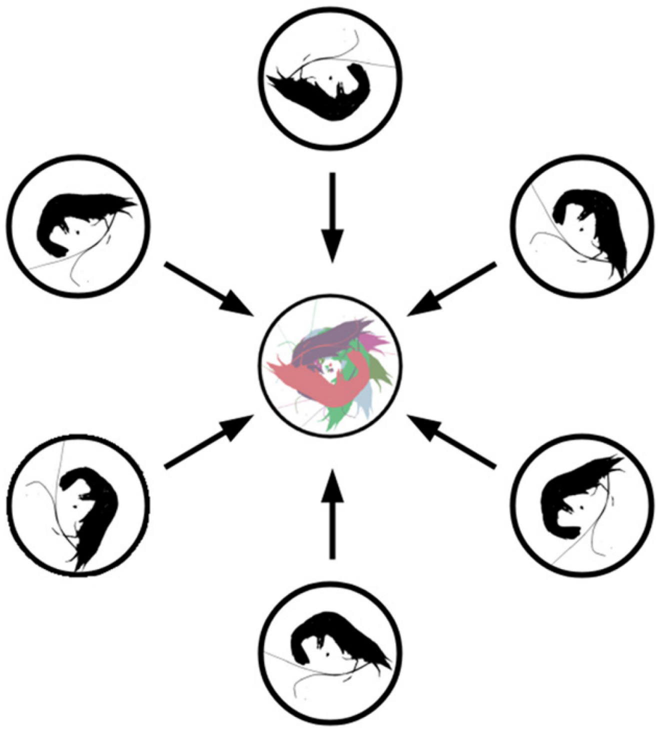

Figure 4. Illustrative figure of the shrimp positions with the rotating base. Source: Authors, 2025.

2.3 Selection, processing, and segmentation of digital images of shrimp

The images of refrigerated shrimp were subjected to a rigorous pre-processing process, aiming to guarantee the quality and representativeness of the samples for subsequent analyses. Image enhancement techniques were initially applied using the bilateral and Gaussian filters (Figure 5) of OpenCV (Python Software Foundation, 2024), to reduce noise and improve sharpness. The Pillow library was used to adjust the lighting and contrast of the images, optimizing the conditions for the segmentation stage, as these variations influence the visual parameters in the image analysis, presenting different levels of perception (Nie et al., 2022).

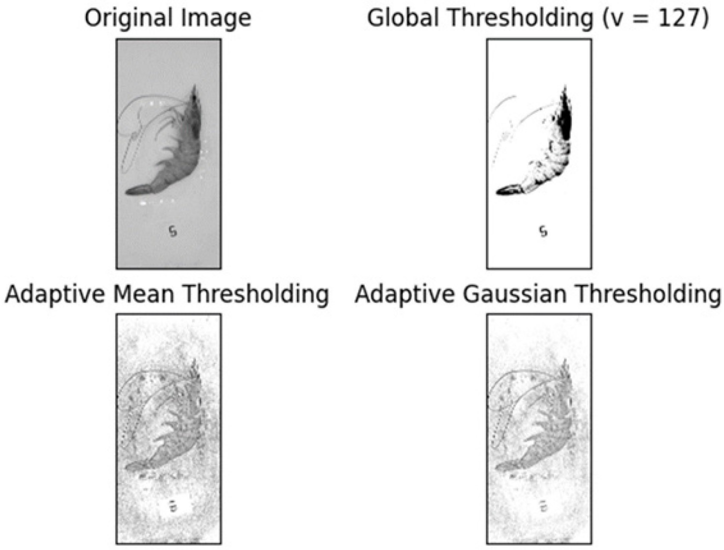

Figure 5. Images demonstrating OpenCV's bilateral (overall and median) and Gaussian filters to reduce noise and improve sharpness. Source: Authors, 2025.

Image segmentation is crucial for identifying and analyzing shrimp. This was performed using thresholding techniques (Figures 6 and 7) that involved simple, adaptive, and the Otsu method (Otsu, 1979). This segmentation of the images consisted of separating the pixels of interest (belonging to the refrigerated shrimp) from the pixels of the environment (belonging to the lighting and the bottom of the support box) so that they could be treated, helping in identifying and qualifying the samples in the images, as well as in the analysis of their morphological attributes. Image segmentation is an edge detection method that enables defining homogeneous regions and contours in the images (Bhatti et al., 2021; Thanikkal, Dubey, Thomas, 2018).

The threshold was used to create a mask to identify regions of interest, in this case, reflections, which is adjusted as necessary for a specific set of images (Jasim, Mohammed, 2021). The mask was then refined to remove any noise with the application of morphology techniques, such as closing and opening, in addition to elliptical structuring elements of different sizes (Chhikara, 2022). Finally, the OpenCV inpainting technique is used to remove the reflections identified by the mask through color information from neighboring pixels to complement the image (Figure 7), completing the treatment.

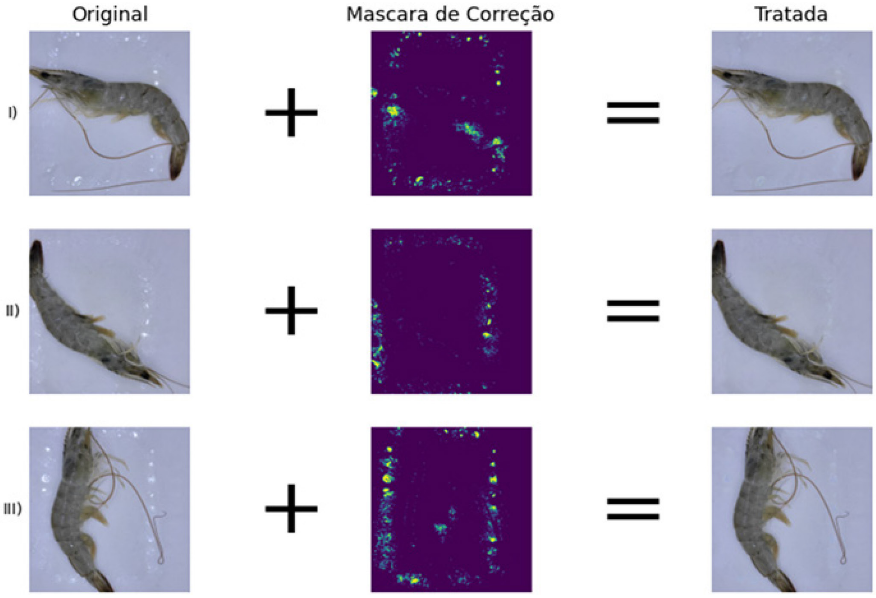

Figure 6. Images showing the treatment of 3 samples by thresholding to reduce light noise, in which there is a process from left to right in each line where the luminosity no longer appears after applying the mask; I) First sample with a lot of distortion around it; II) Second sample with small distortions; III) Third sample with greater distortion in the lighting points. Source: Authors, 2025.

Figure 7. Images showing the focus of item I in figure 5, through thresholding to reduce light noise, in which each line has a process (from left to right), verifying that the luminosity no longer appears after applying the mask. Source: Authors, 2025.

2.5 Digital shrimp image dataset cataloging, creation, and storage

The next phase after the images were corrected was data categorization, in which a dataset was created by carefully classifying the stages of the refrigerated shrimp. The dataset had a main folder called "Main" and was divided into subfolders named according to the time elapsed since the beginning of decomposition in T0 for day zero, T3 for the third day, and T6 for the sixth day. Finally, the complete folders were compressed in zip format, which reduces the file size for storage and facilitates sharing with other researchers or institutions. The images were cataloged in a dataset that was submitted to the Mendeley data repository.

2.6 Neural network development

A comparative evaluation was conducted between several programming languages during the development of the Convolutional Neural Network (CNN), including C++, Java, Kotlin, and Python. Python emerged as the best suited for this project due to its simplicity, readability, and vast ecosystem of specialized libraries such as TensorFlow, Keras, PyTorch, and OpenCV.

The global Python developer community is large and active, providing a rich repository of shared knowledge. This includes tutorials, detailed documentation, discussion forums, and contributions to open source projects, facilitating collaborative solving of programming and image processing challenges.

The code responsible for creating data augmentation uses the "ImageDataGenerator" function responsible for generating new variants of the same database, in which a value was defined for model validation, and the rest is responsible for the training that it should approach, constituting a methodology described by the TensorFlow library itself.

2.3.1 CNN construction

The TensorFlow library and its high-level API, Keras, were chosen as the core tools for building the CNN due to their robust capabilities and flexibility. Keras provides an intuitive interface for defining and training neural networks, making it easy to build and tune complex models. It supports a wide range of image processing operations, such as resizing, normalization, and data augmentation, which are essential for properly preparing images for training. Integration with TensorFlow enabled efficient execution of complex tensor computations and took advantage of hardware acceleration, such as GPUs, to quickly and efficiently train large-scale models.

Key parameters were defined when configuring the CNN, such as scaling images to fit the network input and the type of preprocessing applied, such as normalization and data augmentation. For example, 1000x1000 pixel images were resized to 256x256 pixels using methods that preserve essential data. This adjustment was crucial to simplify processing without losing important information and reducing the need for high processing power. The network architecture was designed with a topology that includes a variable number of neurons and layers, enabling experimentation with and optimization of the model.

The model starts with a Conv2D layer, which applies filters to extract important image features, such as edges and textures. Next, a MaxPooling2D layer reduces the dimensionality of the image, keeping the most relevant features and reducing computational complexity. This convolution and pooling process is repeated three times, each time with more filters, to capture more complex features. After feature extraction, the flatten layer transforms the resulting two-dimensional matrix into a one-dimensional vector. This vector is then passed through a dense layer, which performs a linear combination of the extracted features to identify more abstract patterns (Figure 8).

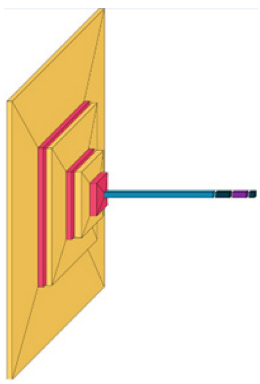

Figure 8. Construction of the convolutional neural network model showing the convolution steps, pooling, flattening, and dense layers, including regularization techniques such as dropout and the use of balanced class weights. Source: Authors, 2025.

Another way to demonstrate this storage arrangement can be seen in (Figure 9), in which the hierarchical feature extraction process took place, playing a key role in understanding and recognizing complex patterns. The CNN was designed to capture this discriminative information through a sequence of specialized layers, where the first image shown was subjected to a convolutional layer. Convolutional filters were then locally applied to identify specific patterns, such as edges and textures, in local regions of the image.

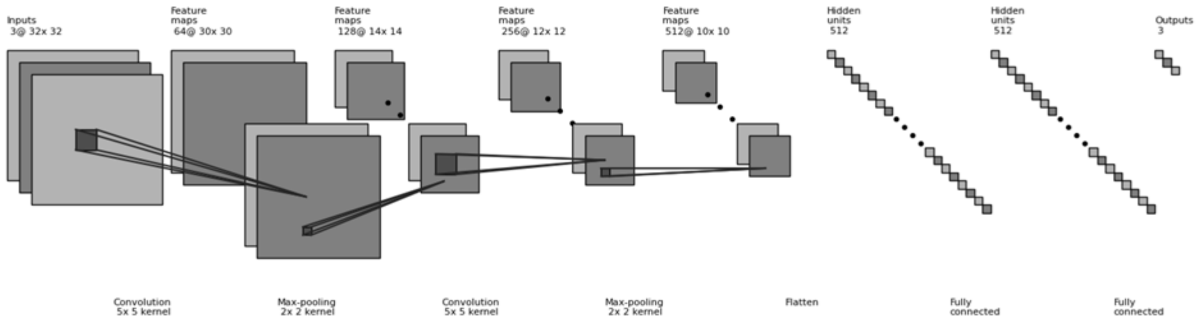

Figure 9. Hierarchical extraction process. Source: Authors, 2025.

When slid across the image, these filters generated feature maps that highlighted relevant patterns in different parts of the scene. Pooling layers were used to reduce spatial dimensionality and preserve the most salient features by performing selective subsampling.

This feature extraction (Figure 9) and subsampling process is repeated in successive layers, allowing the network to hierarchically learn increasingly complex patterns. Finally, fully connected layers embed these extracted features into a latent space, where neurons represent linear combinations of these features. The weights of these connections were adjusted during training, allowing the network to automatically adjust to specific patterns in the dataset.

A dropout layer was then used to avoid overfitting, randomly deactivating a fraction of the neurons during training. Finally, the last dense layer with SoftMax activation produces the probability that the image belongs to each of the possible classes.

The Adam (Adaptive Moment Estimation) algorithm was used as the optimizer due to its ability to dynamically adjust learning rates based on estimating the first and second order moments of the gradients. This contributed to a faster and more stable convergence during training. In addition, the model training was monitored by an Early Stopping function, which stops the training if there is no improvement in the validation loss, restoring the best weights.

To validate the effectiveness of the custom architecture, we conducted detailed comparisons with a pre-trained model called MobileNetV2 (Sandler et al., 2018), which is widely used and available in the TensorFlow library, to evaluate its performance on this task that requires high sensitivity to subtle differences.

2.3.2 Model training and evaluation

After training was completed, the model was saved in .tf format, which describes what is native to TensorFlow, allowing the persistence of not only the network architecture, but also the weights and hyperparameters. At the end, graphs (loss and accuracy) were generated based on Equation 1, detailing the model's performance throughout the training epochs and providing valuable insights into the evolution of learning and potential areas for future adjustments.

$$\text{Accuracy} = TP/(TP+FP+FN) \quad (1)$$

In which: TP = True Prediction, FP = False Positive and FN = False Negative.

2.3.3 Performance evaluation and visualization techniques

Several visualization techniques and metrics were used to evaluate the model performance. First, a confusion matrix was plotted, enabling to visualize the correct and incorrect predictions of the model for each shrimp class at different times (T0, T3 and T6), which then helped to identify specific error patterns. Next, detailed metrics such as recall, precision and F1-score were extracted from a classification report, providing a comprehensive view of the model performance in each class. These metrics were then plotted in bar charts to facilitate visual comparison between classes based on equations 2, 3, and 4 for each class. Soon after, the source code for this study was created and submitted to the GitHub repository.

$$\text{Recall} = TP/(TP+FN) \quad (2)$$

$$\text{Precision} = TP/(TP+FN) \quad (3)$$

$$\text{F1-score} = 2*(\text{Precision} * \text{Recall})/(\text{Precision} + \text{Recall}) \quad (4)$$

3. Results

3.1. Data collection

The smartphone, together with the support box (Figure 10), which contained a rotating base made of MDF (Medium-density Fiberboard), was a crucial and efficient element for capturing the images. Constructing and using prototypes for a specific purpose currently make studies more dynamic and practical. These can be obtained in different ways through laser cutting machines and also through 3D printing, which is currently the innovation in several segments (Silva et al., 2023).

A total of 4,891 photos were taken throughout the process of more than 150 samples of refrigerated shrimp, with different positions and sides, undergoing a selection process to choose the most suitable ones, and removing some unnecessary repetitions from the process, in addition to providing two different sets of data in relation to variations in the texture and lighting of the samples.

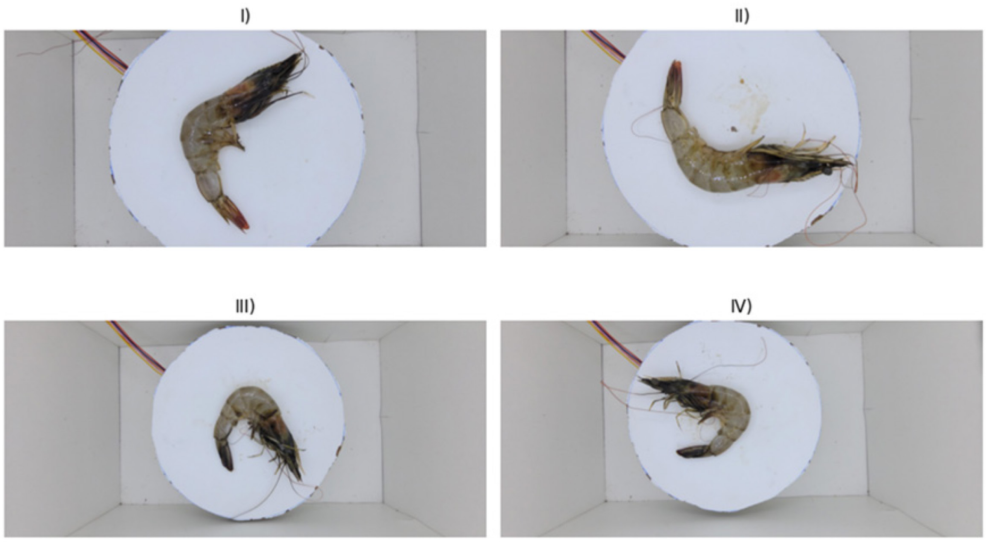

Figure 10. Photographic image of the shrimp inside the support box with the rotation base. I) head to the lower left side and telson to the upper right side; II) head to the left side and telson to the lower side; III) head to the upper left side and telson to the upper side; IV) head to the lower right side and telson to the upper right side. Source: Authors, 2025.

This methodology resulted in a wide variety of capture angles, as illustrated in Figure 9 above, in which the two employed techniques complement each other effectively. The variation in shrimp size induced by the variable height of the motor requires adjustment by capturing images in triplicate; redundancy was essential, since the isolated use of a single image could lead to a reduced data set, which in turn could introduce bias in the results, presenting excessively discrepant data.

3.1.1 Separation and segmentation of shrimp images

It is possible to assess the sharpness and reduce noise in the images using the OpenCV and Pillow libraries. The Pillow library adjusted the brightness and contrast of the pixels, where the sharpest and most contrasted images were selected for segmentation and construction of the dataset.

Segmentation is the process of distinguishing and separating samples from the background or other elements in the image, and is crucial to assess the quality of the samples; this facilitates identifying and quantifying characteristics such as size, shape, and color. The most common segmentation methods include adaptive

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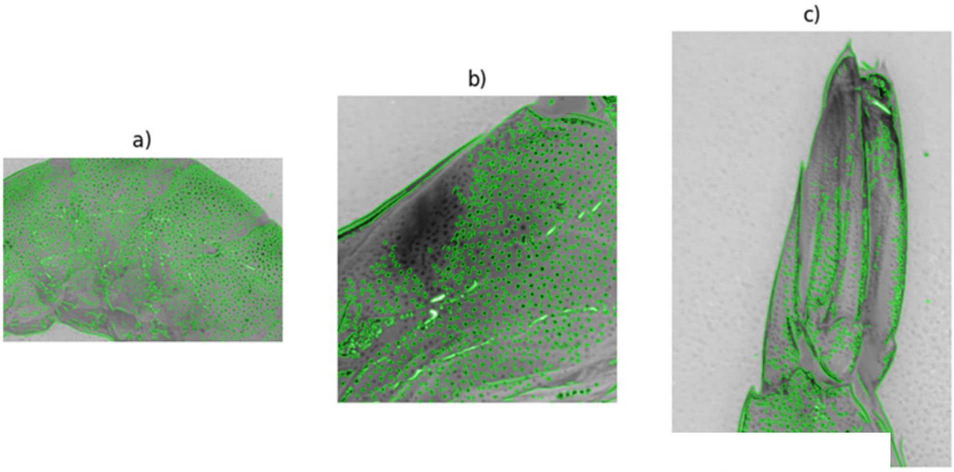

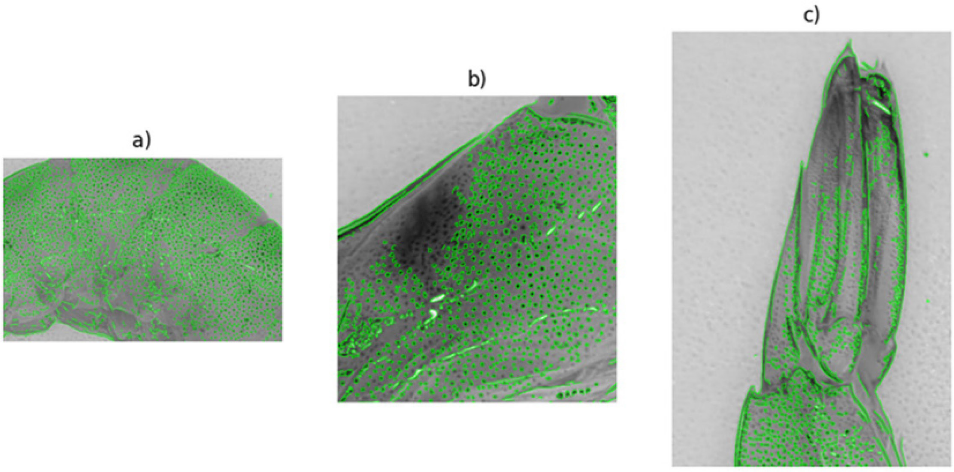

Figure 11. Edge detection images to enter noise. Source: Authors, 2025.

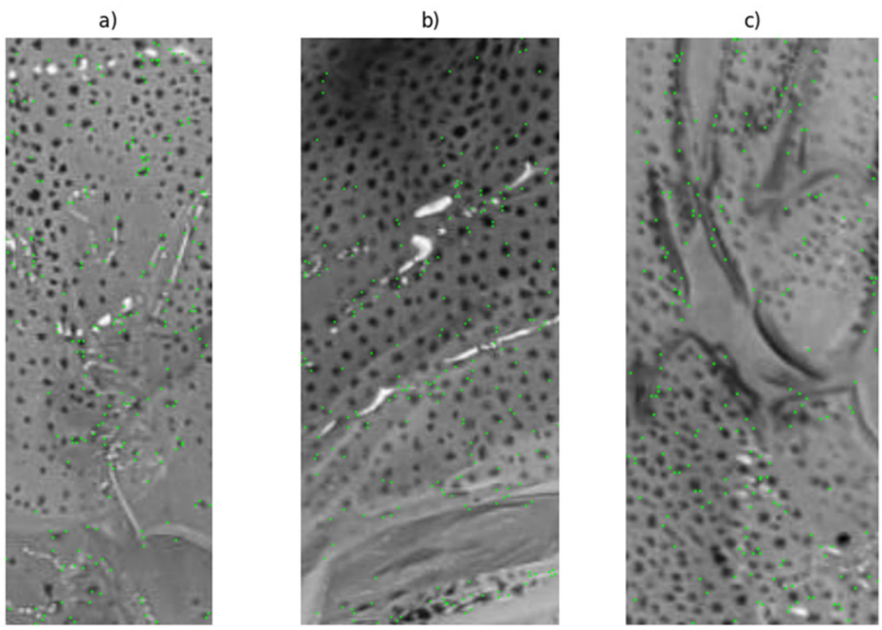

Figure 12. Focus applied to individual edges to better visualize noise. Source: Authors, 2025.

Preprocessing is essential to improve image quality for this type of study, in addition to reducing noise to extract better features and increase the accuracy of image recognition (Zhao et al., 2024). The sharpness of the shrimp images can be seen in (Figures 6 and 7) cited previously in the methodology, which was improved by adjusting the focus, increasing the contrast, and applying edge enhancement filters. According to Ranjan et al. (2017), sharpness is the ability to distinguish fine details and edges of objects in images, where a sharp image presents good definition and clarity, while a blurred image presents low resolution and loss of details. Sharpness can be affected by several factors, such as the equipment quality, the distance between the object and the sensor, the movement of the object or sensor, the exposure and sensitivity of the image, among others. These factors were solved in this study with the help of the support box and the smartphone used.

Noise is an unwanted variation in the pixel values of an image, which can impair its quality and make analysis difficult. Noise can be caused by several factors, such as low sensor quality, high sensitivity, inadequate exposure, and image compression (among others). There are different types of noise, such as Gaussian noise, salt and pepper noise, Poisson noise, etc. (Ranjan, Patel, Chellappa, 2017). Thus, filtering methods were used to reduce the noise of an image, such as the mean filter, the median filter, and the Gaussian filter. In this study, we chose to use the Gaussian filter, which enables a smoother correction and is shown in (Figures 13 and 14).

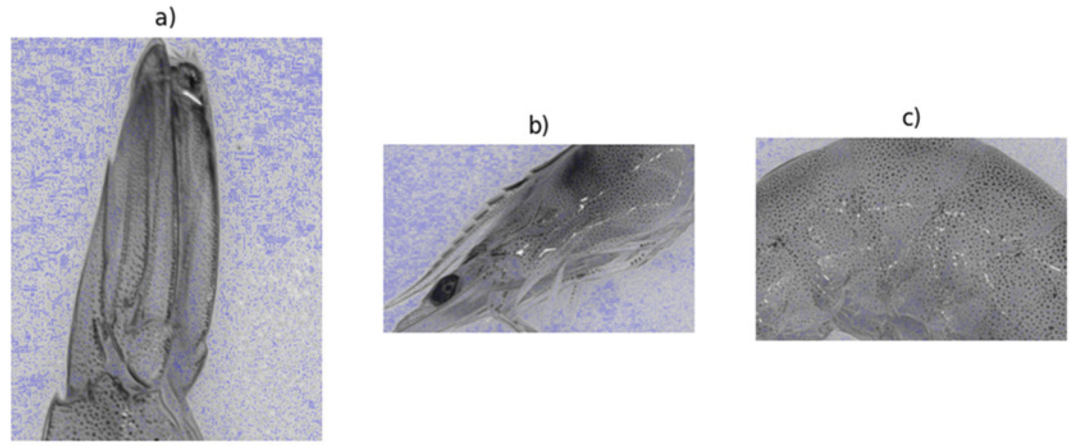

Figure 13. Images showing locations on the shrimp where Gaussian filters were applied. Source: Authors, 2025.

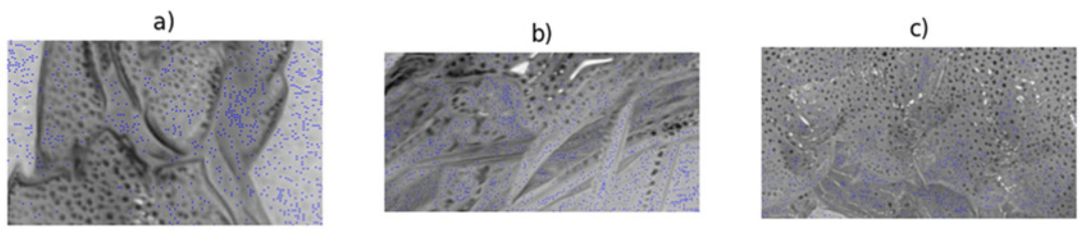

Figure 14. Enlarged images showing locations on the shrimp where Gaussian filters were applied. Source: Authors, 2025.

Contrast is the difference between the brightness or color values of the pixels in an image. Contrast is important to highlight the details and edges of the objects in the image, as well as to facilitate the observer's visual perception. Contrast can be measured by different indices, such as Michelson contrast, Weber contrast, RMS contrast, etc. The contrast of an image can be changed through processing techniques, such as brightness adjustment, gamma adjustment, and histogram equalization (Neczypor et al., 2021). Contrast media can be used in shrimp studies to highlight specific features in high-resolution images, such as melanosis, which are dark spots (Isfran et al., 2023), and astaxanthin release, which is a carotenoid typical of crustaceans (Kimbuathong et al., 2020).

Lighting is an essential factor for image quality, as it directly influences the image sharpness, noise, contrast and colors. Lighting can be natural or artificial, direct or diffuse, uniform or variable, etc. Adequate lighting depends on the type of image you want to obtain, the purpose of the image, and the environment where the image is captured, among other aspects. Lighting can be controlled by devices such as flashes, reflectors, diffusers, etc. Lighting can be modified through processing techniques (Zhang et al., 2021) such as white balance (in which it is possible to adjust the image colors to make them appear more natural); color correction (in which it is possible to modify the colors to correct lighting problems or to highlight certain features of the image); and exposure adjustment (where it is possible to change the image brightness to improve the visibility of details).

These operations were performed using image processing libraries that were mentioned in the methodology (OpenCV and Pillow), using adjustments in the lighting exposure to a smoother value throughout its distribution (Figures 15 and 16).

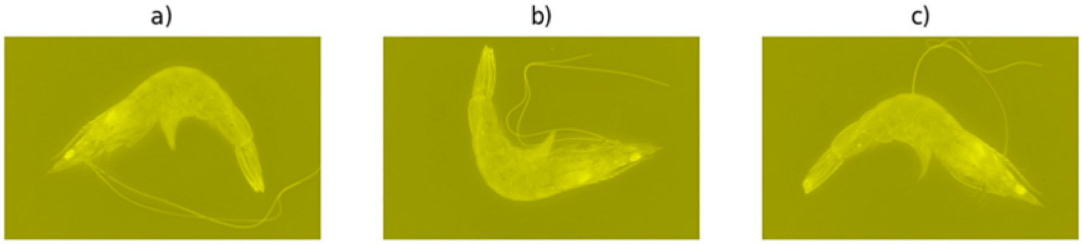

Figure 15. Images of color intensity at certain points. Source: Authors, 2025.

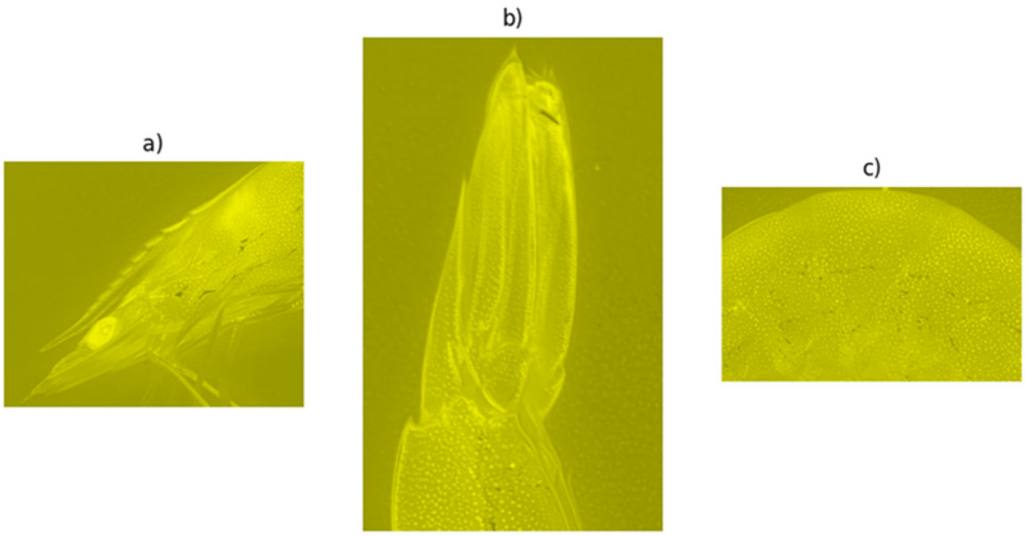

Figure 16. Full image of color intensity analysis. Source: Authors, 2025.

Classification in this context involves grouping shrimp into categories based on defined criteria such as size, quality, or decomposition stage. These images are valuable to researchers seeking to improve analysis and classification methods as they show the lighting variation in different parts of the shrimp.

3.1.2 Digital shrimp image dataset cataloging, creation, and storage

The shrimp deterioration progression was carefully observed over the course of days during the study, recording each significant change, which is essential for understanding the decomposition patterns and visual manifestations of each stage, such as melanosis. Analyzing these changes not only enabled identifying the deterioration stages, but also provided valuable insights into the conditions that accelerate or slow down the process.

After selecting the images, the dataset was created and submitted to the Mendeley Data repository through the Repository name Degradation of Shrimp with the Data identification number: 10.17632/gyntc9yzx4.2 and Direct URL to data: https://data.mendeley.com/drafts/gyntc9yzx4.

The "Dataset_degradation_of_shrimp.zip" file contains an organized structure of subfolders, each labeled according to the time elapsed since the beginning of decomposition: T0 for day zero, T3 for day three, and T6 for day six. These subfolders are contained within a main folder called "Main," and their organization is demonstrated in Figure 17. Each subfolder includes three sets of images corresponding to collections performed in three different months in order to capture a wider range of variations in shrimp decomposition, where the first collection faced setbacks resulting in the loss of samples in T6, thereby requiring a complementary collection to fill in the gaps. This methodology ensures a comprehensive analysis that is not limited to a single data collection period.

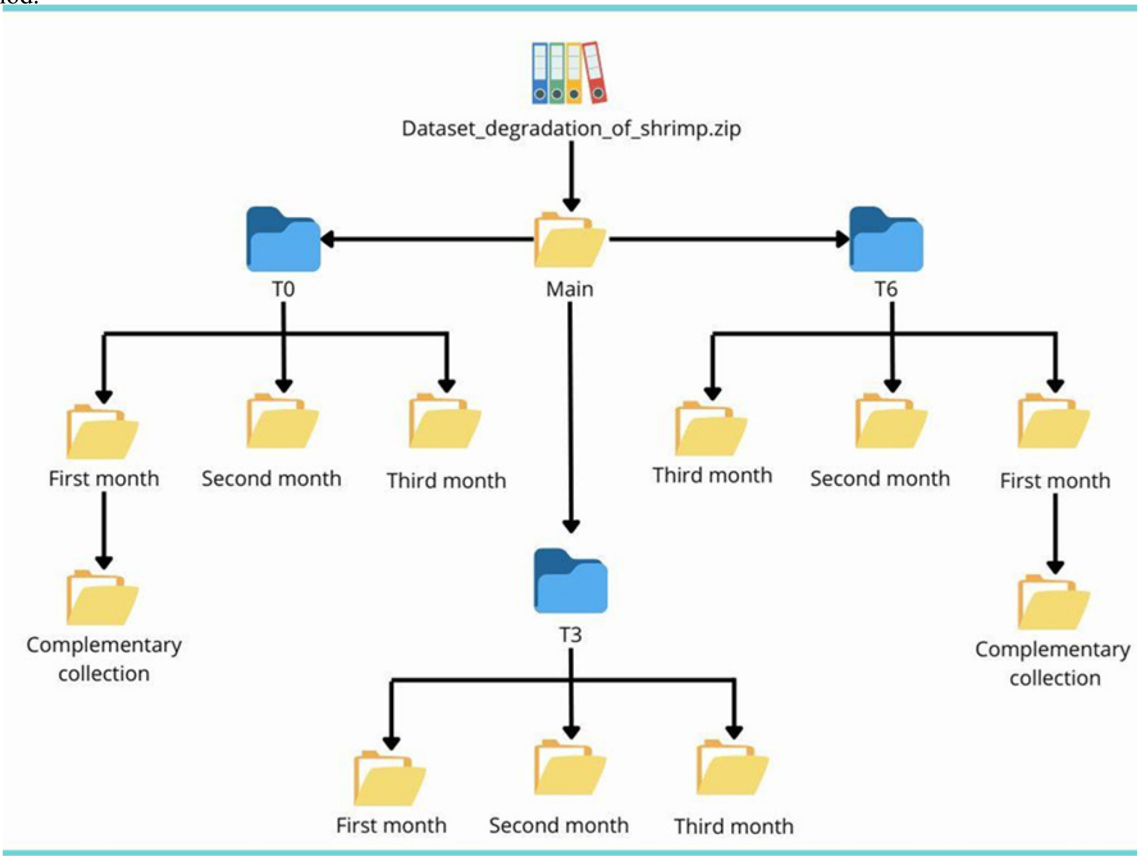

Figure 17. Organizing dataset folders and subfolders. Source: Authors, 2025.

Table 1 presents the quantitative distribution of images of shrimp in different decomposition stages, organized into three distinct collections. Each collection represents a set of images captured on different days since the beginning of decomposition, marked as T0, T3, and T6, as previously described.

Table 1. Quantitative distribution of shrimp images at different decomposition stages.

Day	First collection	Second collection	Third collection	Additional T0	Additional T6
T0	98 images	187 images	420 images	441 images	-
T3	56 images	180 images	90 images	-	-
T6	-	180 images	176 images	-	361 images

Source: Authors, 2025.

This dataset contains 2,189 images of shrimp (*L. vannamei*). These images can be used to assess the perishability of shrimp, given their short shelf life. This is especially relevant for understanding the biochemical reactions and microbiological changes that occur during degradation. It is the first openly accessible dataset that documents shrimp degradation. It provides valuable material for research related to the intelligent identification of these animals. The evaluation of shrimp images at different deterioration stages can help researchers, students, and professionals in understanding the degradation process of this food. This can have significant implications for the seafood industry and the quality of products offered to the consumer.

These images can be a valuable tool for education and training. Students, professionals, and enthusiasts in the field can learn to identify specific characteristics of shrimp under different conditions, contributing to the development of practical skills. These data can also serve as a basis for developing automated algorithms capable of automatically classifying the degradation state of shrimp in real time. This could be applied to quality control systems or even portable devices for producers and industries.

Below are some images (Figure 18) of the shrimp which are part of the dataset. They are in different deterioration stages, starting from day 0 (when they were caught) until the 6th day when the progression of changes such as melanosis is observed, which are dark spots that can be seen on both the cephalothorax and the telson, and are indicative of deterioration (Shao et al., 2021). Melanosis is considered one of the biggest problems for the shrimp farming industry and is characterized by the post-mortem biochemical reaction with enzymatic action, where the phenolic compounds present in the shrimp are oxidized into quinones and these produce dark pigments (Isfran et al., 2023). This significantly affects shrimp commercialization.

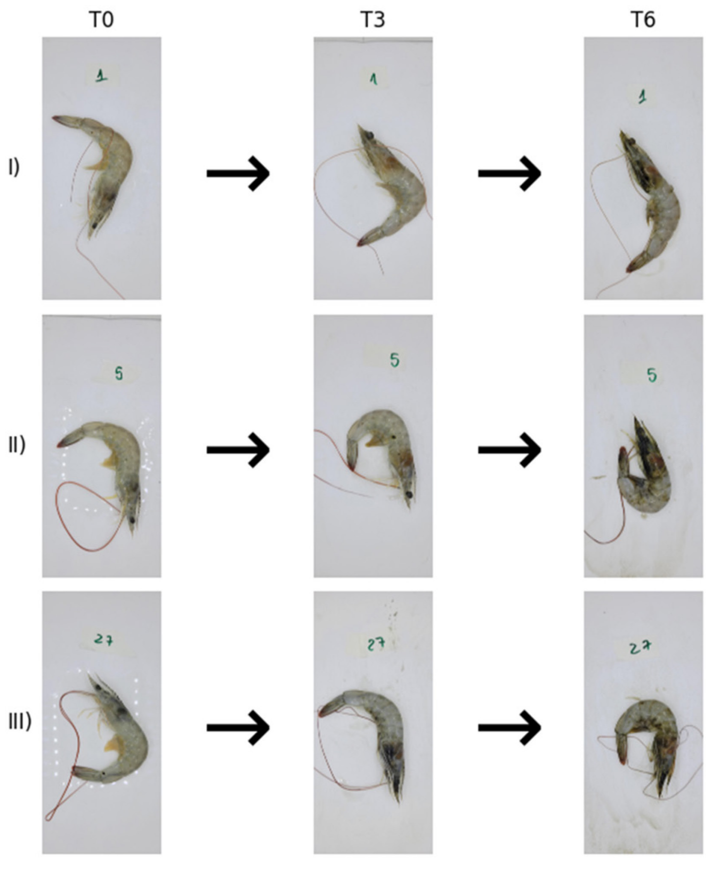

Figure 18. Images of the shrimp in the dataset. Source: Authors, 2025.

3.2 Neural network development

3.2.1 Image generation

Part of the code responsible for defining two objects that use the data augmentation of the “ImageDataGenerator” is presented in (Figure 19) below: “DadosParaTreinamento” with 80% and “DadosParaValidacao” with 20%, responsible for applying transformations to the training and validation images with different proportions for more accurate validation.

```
# Geradores de Fotos Para Treino
GeradorTreino = DadosParaTreinamento.flow_from_directory(
    DiretorioTrein,
    target_size=(imagLargura, imagAltura),
    batch_size=Lotes,
    class_mode='binary'
)

GeradorValidacao = DadosParaValidacao.flow_from_directory(
    DiretorioValidacao,
    target_size=(imagLargura, imagAltura),
    batch_size=Lotes,
    class_mode='binary'
)

# Construindo o modelo CNN
model = Sequential()
model.add(Conv2D(32, (3, 3), input_shape=TipoDeEntrada, activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dense(1, activation='sigmoid'))

model.compile(loss='binary_crossentropy',optimizer='adam', metrics=['accuracy'])
```

Figure 19. Codes for training and validation. Source: Authors, 2025.

The next step was to create data generators for training (GeradorTreino) and validation (GeradorValidacao), shown in (Figure 19). These generators provide data in batches during training, applying the specified transformations of the previously shown parameters. This is a fundamental part of effectively preparing training and validation data, incorporating techniques such as data augmentation to enrich the diversity of the set, which is crucial for the successful training of convolutional neural network models.

Continuing in the image generation phase, we moved on to the CNN execution stage, where its programming provided flexibility in the training process and could be changed depending on the need. A size of 360 by 360 pixels was initially applied using the “nearest” method, which uses a strategy of close neighbors so as not to affect the image quality. Normalization uses a batch format (Batch Normalization) and is frequently used to normalize the activation values in each mini-batch, reducing dependence on the initialization of the weights and mitigating internal covariance problems.

Next, we used the TensorFlow ImageDataGenerator function to generate additional images to collect and filter the images. This function proved to be an essential tool that enabled us to apply real-time transformations to the images during neural network training, contributing to increasing the dataset diversity.

3.2.2 CNN construction

The construction of the CNN is shown in Figure 20, in which the storage arrangement design used in this study, after resizing and applying the filter layers, can be seen. The dropout layer used resulted in a range of 0.1 (10%) that avoided overfitting, randomly deactivating a fraction of the neurons during training, and the last dense layer with SoftMax activation produced the probability of the image belonging to each of the possible times (T0, T3, and T6). The best weights were analyzed every 5 epochs during monitoring with the help of the Early Stopping function.

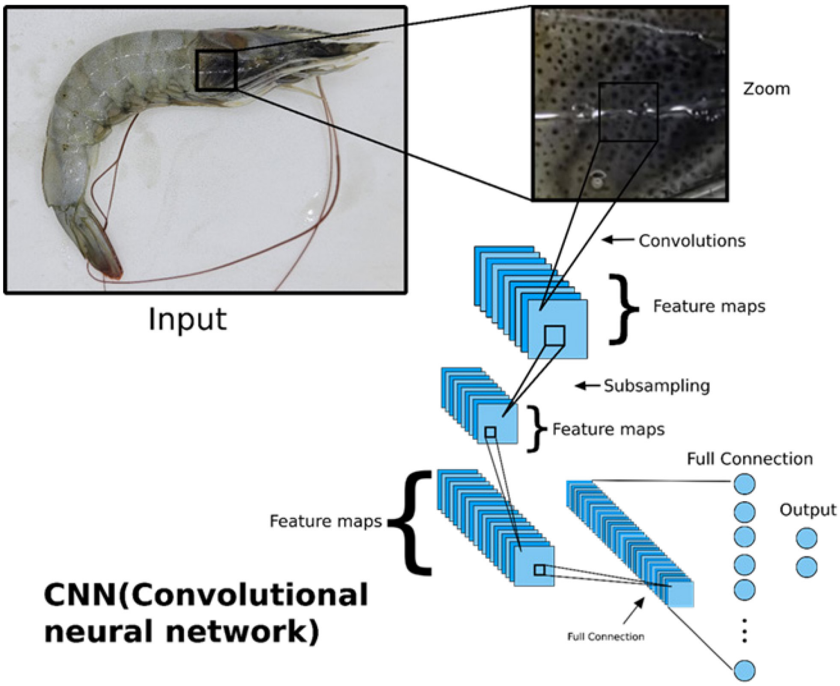

Figure 20. CNN design of refrigerated shrimp. Source: Authors, 2025.

3.2.3 CNN training

The dataset in the training process was initially segmented into three distinct parts: training, validation, and testing. This strategic division aims to optimize model learning and avoid overfitting.

Successive iterations were conducted during the training phase, with fine-tuning of hyperparameters to achieve the best possible performance. The model's effectiveness was meticulously analyzed based on evaluation metrics, including accuracy and error, which is represented through detailed graphs for a deeper and more comprehensive analysis. The loss in both models exhibited values lower than 0.4 (Figure 21 - A and B). The training phase accuracy for both models demonstrated values exceeding 95% (0.95) (Figure 21 – C and D).

Several studies have already been published and directed at meat quality, in which they detected the freshness of raw material of animal origin in real time, resulting in 96.03% (Abdallah et al., 2023) and 93.13% accuracy (Sagiraju et al., 2023) using different AI models. Therefore, the customized model exhibits patterns similar to those of previously developed models.

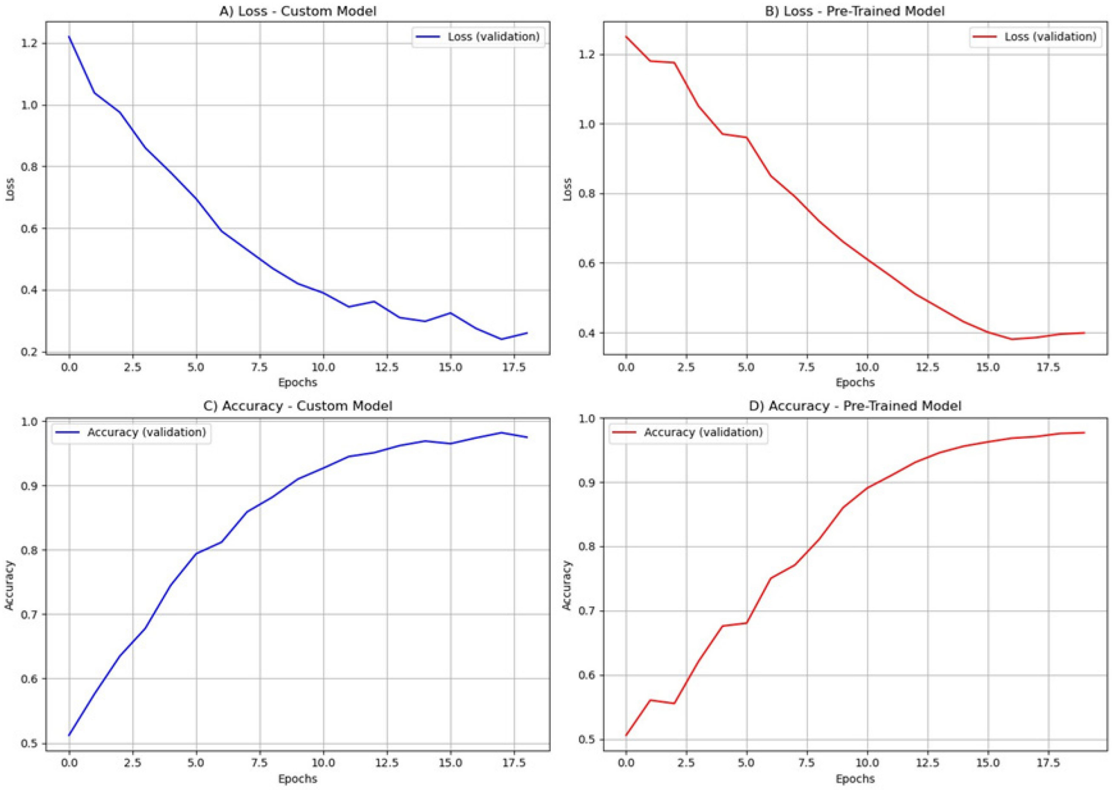

Figure 21. Graphs produced during the training and validation phases, depicting loss (A and B - Custom Model and Pre-trained Model) and accuracy (C and D - Custom Model and Pre-trained Model) in the analysis process of CNNs. Source: Authors, 2025.

The confusion matrix (Figure 22) illustrates where errors occurred during training and validation. The central dark blue areas represent the true positives (TP); the light blue areas in the upper right represent the false positives (FP); and the light blue areas in the lower left represent the false negatives (FN) according to each class (T0, T3, and T6).

The T0 and T6 classes obtained more hits when compared to T3, which can be explained by the more discrepant colorimetric changes observed in Figure 18. Büyükarıkan (2024) presented in his study an effective approach to beef quality classification by evaluating global and artisanal color resources based on a CNN and through the confusion matrix obtained high performance values of accuracy, precision, recall and F1-score, which were above 94% in all results, emphasizing that the different types of classes evaluated still had variations between them in each metric.

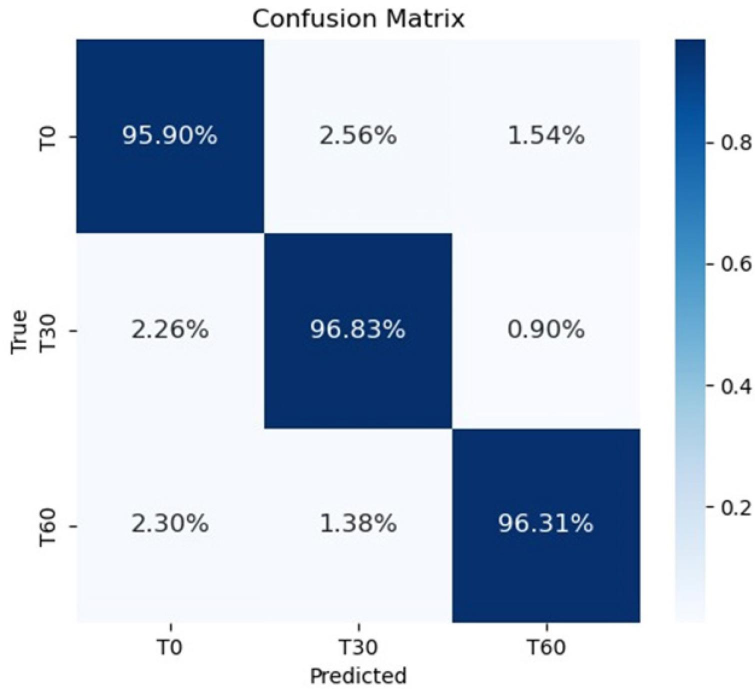

Figure 22. Confusion matrix schematic. Time 0 days (T0); Time 3 days (T3); Time 6 days (T6). Central dark blue areas represent the true positives (TP); Light blue areas on the upper right represent false positives (FP); Light blue areas on the lower left represent the false negatives (FN). Source: Authors, 2025.

The metrics that were extracted can be seen in figures 23, 24, and 25 below, resulting in what was already mentioned in the previous paragraph, namely that T0 and T6 expressed higher recall, precision, and F1-score than T3. These figures (23, 24 and 25) depict the model's performance in each class according to the confusion matrix (Figure 22), detailing its parameters in different ways; their specific calculations were performed according to equations 2, 3 and 4 mentioned in the methodology, where each one refers to its own TP with there being one for each class (T0, T3 and T6).

The FP and FN values correspond to the yellow and red expectations (Figure 22) in their vertical and horizontal positions, showing how the model behaved throughout the process with the data augmentation used. The results described in recall refer to the proportion of positives correctly identified, showing how good it is at identifying correct data. Precision data is responsible for identifying the proportion of positives that are actually correct, showing how well it worked. In turn, the F1-score presents the balance between precision and recall, a broader view of how the training is, showing a controlled average that adapts to the weights of each of the two results.

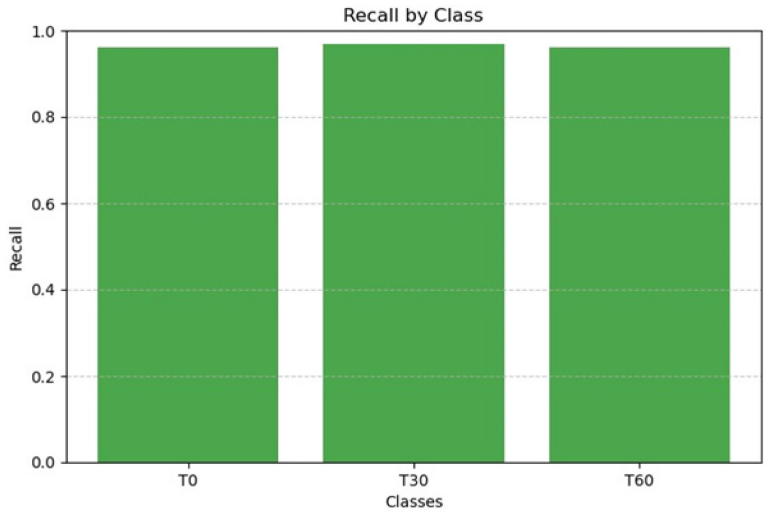

Figure 23. Recall parameters. Time 0 days (T0); Time 3 days (T3); Time 6 days (T6). Source: Authors, 2025.

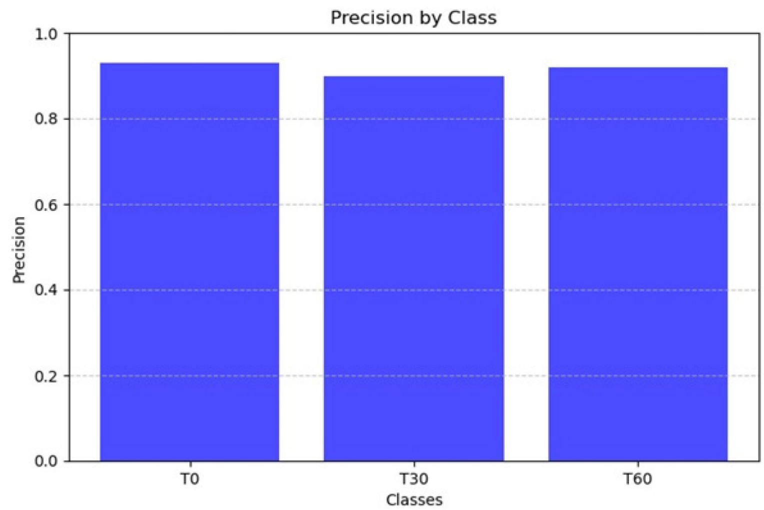

Figure 24. Precision parameters. Time 0 days (T0); Time 3 days (T3); Time 6 days (T6). Source: Authors, 2025.

The customized model developed in this study presented performance equivalent to the pre-trained MobileNetV2 model (Figure 25), proving its effectiveness. However, the main merit lies in its flexibility and complete control over the architecture, allowing precise adjustments to meet the demands of the dataset. This approach facilitates continuous improvements, future adaptations, and reduces dependence on external suppliers, ensuring autonomy in development. Thus, in addition to maintaining high performance, personalized CNNs offer strategic advantages in control, adaptability, and independence, essential for advancing research in food chemistry.

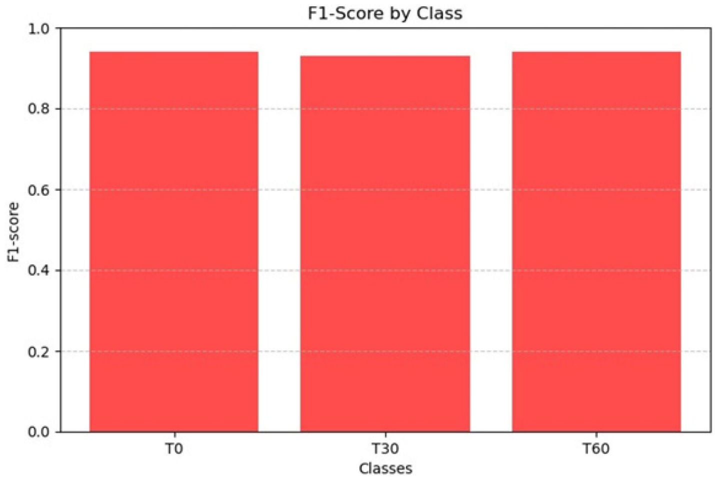

Figure 25. F1-score parameters. Time 0 days (T0); Time 3 days (T3); Time 6 days (T6). Source: Authors, 2025.

4. Discussion

4.1 Data collection and image acquisition

The smartphone, together with the support box (Figure 10), which contained a rotating base made of MDF (Medium-density Fiberboard), was a crucial and efficient element for capturing the images. The use of controlled imaging environments is well established in shrimp quality studies, where standardized chambers with fixed camera positioning and uniform lighting have been shown to ensure consistency across image datasets (Zaki Dizaji et al., 2019). Constructing and using prototypes for a specific purpose currently make studies more dynamic and practical. These can be obtained in different ways through laser cutting machines and also through 3D printing, which is currently the innovation in several segments (Silva et al., 2023).

This methodology resulted in a wide variety of capture angles, as illustrated in Figure 9 above, in which the two employed techniques complement each other effectively. Capturing images from multiple angles has been recognized as an important strategy to increase dataset variability and reduce bias in shrimp detection models (Kumar et al., 2025). The variation in shrimp size induced by the variable height of the motor requires adjustment by capturing images in triplicate; redundancy was essential, since the isolated use of a single image could lead to a reduced data set, which in turn could introduce bias in the results, presenting excessively discrepant data.

4.2 Image segmentation

Segmentation is the process of distinguishing and separating samples from the background or other elements in the image, and is crucial to assess the quality of the samples; this is corroborated by automated shrimp monitoring systems, where image segmentation is applied to separate organisms from the background as a fundamental step before detection and quantification (Ahmad et al., 2025), reinforcing its importance in image-based analysis. This facilitates identifying and quantifying characteristics such as size, shape, and color. The most common segmentation methods include adaptive thresholding and edge detection algorithms, which are effective in isolating the shrimp aspects from the background, but this is not a necessity due to the controlled environment of the support box.

The thresholding and edge detection methods in the segmentation process were essential and enabled detecting the homogeneous parts and contours of the shrimp. This process can be observed in the figures mentioned above (Figures 6 and 7), where the greenish points are considered to be pixels with values above the threshold, therefore belonging to the object (Figure 6), and also enabling detection of edges in pixels with abrupt variations in intensity, thereby indicating the transition between the object and the background. The segmentation pipeline employed here shares methodological similarities with approaches described in the literature, where grayscale conversion followed by edge detection and morphological operations — such as dilation and erosion — have proven effective in isolating aquatic organisms from complex backgrounds (Kumar et al., 2025). Figures 11 and 12 illustrate the segmentation result of the shrimp images, demonstrating the green pigments that belong to the shrimp.

4.3 Image preprocessing — sharpness, noise, contrast, and lighting

Preprocessing is essential to improve image quality for this type of study, in addition to reducing noise to extract better features and increase the accuracy of image recognition (Zhao et al., 2024). The sharpness of the shrimp images can be seen in Figures 6 and 7 cited previously in the methodology, which was improved by adjusting the focus, increasing the contrast, and applying edge enhancement filters. According to Ranjan et al. (2017), sharpness is the ability to distinguish fine details and edges of objects in images, where a sharp image presents good definition and clarity, while a blurred image presents low resolution and loss of details. Sharpness can be affected by several factors, such as the equipment quality, the distance between the object and the sensor, the movement of the object or sensor, the exposure and sensitivity of the image, among others. These factors were solved in this study with the help of the support box and the smartphone used.

Noise is an unwanted variation in the pixel values of an image, which can impair its quality and make analysis difficult. Noise can be caused by several factors, such as low sensor quality, high sensitivity, inadequate exposure, and image compression (among others). There are different types of noise, such as Gaussian noise, salt and pepper noise, Poisson noise, etc. (Ranjan, Patel, Chellappa, 2017). Thus, filtering methods were used to reduce the noise of an image, such as the mean filter, the median filter, and the Gaussian filter. In this study, we chose to use the Gaussian filter, which enables a smoother correction and is shown in (Figures 13 and 14).

Contrast is the difference between the brightness or color values of the pixels in an image. Contrast is important to highlight the details and edges of the objects in the image, as well as to facilitate the observer's visual perception. Contrast can be measured by different indices, such as Michelson contrast, Weber contrast, RMS contrast, etc. The contrast of an image can be changed through processing techniques, such as brightness adjustment, gamma adjustment, and histogram equalization (Neczypor, Real, Doro, 2021). Contrast media can be used in shrimp studies to highlight specific features in high-resolution images, such as melanosis, which are dark spots (Isfran et al., 2023), and astaxanthin release, which is a carotenoid typical of crustaceans and plays an important role in their natural pigmentation, also being explored as a dietary pigmentation enhancer in captive marine species (Kimbuathong et al., 2020; Santamaria Miranda et al., 2025). Visual and colorimetric features extracted from shrimp images under controlled environments have been shown to correlate strongly with time elapsed since capture, supporting the use of image-based indicators as proxies for freshness assessment (Zaki Dizaji et al., 2019).

Lighting is an essential factor for image quality, as it directly influences the image sharpness, noise, contrast, and colors. Lighting can be natural or artificial, direct or diffuse, uniform or variable, etc. Adequate lighting depends on the type of image you want to obtain, the purpose of the image, and the environment where the image is captured, among other aspects. Lighting can be controlled by devices such as flashes, reflectors, diffusers, etc. Lighting can be modified through processing techniques (Zhang et al., 2021) such as white balance (in which it is possible to adjust the image colors to make them appear more natural); color correction (in which it is possible to modify the colors to correct lighting problems or to highlight certain features of the image); and exposure adjustment (where it is possible to change the image brightness to improve the visibility of details).

4.4 Dataset and shrimp deterioration

Below are some images (Figure 18) of the shrimp, which are part of the dataset. They are in different deterioration stages, starting from day 0 (when they were caught) until the 6th day, when the progression of changes, such as melanosis, is observed, which are dark spots that can be seen on both the cephalothorax and the telson, and are indicative of deterioration (Shao et al., 2021). Melanosis is considered one of the biggest problems for the shrimp farming industry and is characterized by the post-mortem biochemical reaction with enzymatic action, where the phenolic compounds present in the shrimp are oxidized into quinones, and these produce dark pigments (Isfran et al., 2023). This significantly affects shrimp commercialization.

4.5 CNN performance and comparison with literature

Several studies have already been published and directed at meat quality, in which they detected the freshness of raw material of animal origin in real time, resulting in 96.03% (Abdallah et al., 2023) and 93.13% accuracy (Sagiraju et al., 2023) using different AI models. Comparable results have been reported in the detection of hepatopancreatic diseases in shrimp, where lightweight CNN architectures such as Mobile Net and Efficient Net achieved over 95% accuracy in classifying infected tissues (Aung et al., 2025). Therefore, the customized model exhibits patterns similar to those of previously developed models.

The confusion matrix (Figure 22) illustrates where errors occurred during training and validation. The central dark blue areas represent the true positives (TP); the light blue areas in the upper right represent the false positives (FP); and the light blue areas in the lower left represent the false negatives (FN) according to each class (T0, T3, and T6). The T0 and T6 classes obtained more hits when compared to T3, which can be explained by the more discrepant colorimetric changes observed in Figure 18. Büyükarıkan (2024) presented in his study an effective approach to beef quality classification by evaluating global and artisanal color resources based on a CNN and through the confusion matrix obtained high performance values of accuracy, precision, recall and F1-score, which were above 94% in all results, emphasizing that the different types of classes evaluated still had variations between them in each metric.

The customized model developed in this study presented performance equivalent to the pre-trained MobileNetV2 model (Figure 26), proving its effectiveness. Corroborating this, hybrid deep learning approaches such as CNN+LSTM have achieved up to 99.07% accuracy in classifying freshness levels of frozen-thawed shrimp, further demonstrating the potential of customized architectures for non-destructive quality assessment in seafood (Genç et al., 2025).

However, the main merit lies in its flexibility and complete control over the architecture, allowing precise adjustments to meet the demands of the dataset. This kind of adaptability aligns with data-driven frameworks that integrate staged predictions and diverse model comparisons to identify the most suitable approach for specific biological datasets (Yang et al., 2025). This approach facilitates continuous improvements, future adaptations, and reduces dependence on external suppliers, ensuring autonomy in development. Thus, in addition to maintaining high performance, personalized CNNs offer strategic advantages in control, adaptability, and independence, essential for advancing research in food chemistry.

5. Conclusions

The detailed analysis of shrimp images from specialized datasets enabled the creation of a highly effective Convolutional Neural Network (CNN) model. It was possible to improve sharpness, contrast, and segmentation through the use of advanced image processing techniques, facilitating accurate identification of the different degradation categories. This process resulted in a diverse and comprehensive dataset, essential for training the CNN. The quality of the images and the processing methodology adopted were crucial to identifying the defects and colorimetric modifications of the shrimp, offering an adequate and innovative tool for quality control in the shrimp farming industry. Therefore, it can be concluded that it is important to develop an automatic system using artificial intelligence and image processing, offering a new perspective for research in other studies, especially those involving color. The focus in future studies will be on analyzing the characteristics of specific regions of each image instead of the entire image for shrimp quality assessment.

6. Acknowledgments

The authors would like to thank the Funding Agency Ceará Foundation for Scientific and Technological Development Support – FUNCAP, and the Federal Institute of Education of Ceará - IFCE Sobral campus, for the structural support to carry out the study.

7. Authors' Contributions

Rafael Pereira Frota: investigation. *Francisca Joyce Elmiro Timbó Andrade*: writing – review & editing. *Georgia Maciel Dias de Moraes*: writing – review & editing. *Raimundo Alan Freire Moreira*: methodology and validation. *Leiliane Teles César*: writing – review & editing. *Mirla Dayanny Pinto Farias*: project administration.

8. Conflicts of Interest

No conflicts of interest.

9. Ethics Approval

Not applicable.

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Funding

Yes applicable.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

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