Deep Learning based Shrimp Classification

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Abstract. This work proposes a novel approach based on deep learning to address the classification of shrimp (Pennaeus vannamei) into two classes, according to their level of pigmentation accepted by shrimp commerce. The main goal of this actual study is to support the shrimp industry in terms of price and process. An efficient CNN architecture is proposed to perform image classification through a program that could be set other in mobile devices or in fixed support in the shrimp supply chain. The proposed approach is a lightweight model that uses HSV color space shrimp images. A simple pipeline shows the most important stages performed to determine a pattern that identifies the class to which they belong based on their pigmentation. For the experiments, a database acquired with mobile devices of various brands and models has been used to capture images of shrimp The results obtained with the images in the RGB and HSV color space allow for testing the effectiveness of the proposed model.

Keywords: Pigmentation · color space · light weight network

1 Introduction

The actual report on shrimp export shows that Ecuador in the last 3 years has become the main supplier of shrimp in the world. By 2022, 209 million pounds were exported representing USD 599 million dollars. It represents of 37% compared with the same period (cited from National Chamber of Aquaculture, 2022). The shrimp industry has evolved in the last two decades, which leads to the mandatory automation of manual processes in any of its production stages. Therefore, technology has become the best ally to improve productivity and quality control. Especially, in those countries where this industry has become one of the pillars of the gross domestic product, reaching export levels that place them as the first in the world. Following the importance of this industry, the use of technology based on computer vision nowadays has been developing very fast to support the automation of critical processes from the farm to the processor. In particular, those most susceptible to human error for quality control or classification of subtypes for dealing with the right price between the farmer and processors, as well, an efficient packaging and distribution processes. One of the most failure-prone processes visually evaluated the shrimp based in color (varies farm to farm) and the manual shrimp class classification made by a specialist. This task has always been tedious and time-consuming, dependent on the specialists who perform it, and prone to human error. These tasks become more complex when the objects to be classified are aquatic species that are susceptible to rapid deterioration due to high temperatures or constant handling. Provide the right deal price and final market is base in score visually and hand made set.

A special case of the object is the shrimp which, being a product of mass consumption in many countries, has become crucial to have automated processes with the least incidence of manual activities to classify them. Therefore, in this work, it is proposed to implement algorithms based on computer vision and deep learning to classify shrimp (Pennaeus vannamei) more quickly, efficiently, and with fewer incidents or failures. With this proposal, a classification method is developed that allows determining, based on a trained model, the type of shrimp according to its pigmentation. These processes are intended to reduce the time and costs of the shrimp at packaging process. Since shrimp industries have evolved last decade, there are various techniques based on computer vision to identify, classify and segment shrimp. For example, in [13], a method is proposed to detect the freshness of shrimp captured by mobile devices, using a deep learning architecture. Another approach that discriminates shelled shrimp (Metapenaeus ensis) by their status between fresh, frozen-thawed, and cold stored using hyperspectral imaging applying successive projections algorithm (SPA) is presented in [9]. Similarly, in Liu et al. [5] the authors propose a shrimp recognition based on a computer vision approach to determine the freshness of shrimp before shipment to distribution centers for human consumption.

In the current work, a novel computer vision-based approach is proposed for shrimp class classification. In this approach, we explore the use of color space imaging to train our model to determine if working in another color space other than the RGB one can improve the results obtained in the validation of the model. We have trained our model using images from the RGB and HSV color spaces. The core idea is to validate the effectiveness of the classification results on each color space image dataset. Additionally, in our research, we have generated our own set of good-quality images of shrimp in the same packaging line and shrimp harvested at the farm. To fulfill this task, we have used a set of cameras from mobile devices to capture the images of the shrimp with different lighting level that considerably increase the shadows in the shots and not facilitates the focus of the shrimp in the images. Likewise, the shrimp images have been captured in different environments or scenarios.

The proposed pipeline consists of firstly capturing shrimp images, then images are labeled by experts, and these images are used then for training the proposed architecture. We propose a lightweight network that classifies the shrimps into two out of the four classes according to their pigmentation. Due to the imbalance present in the data set, where the samples of one of the classes are

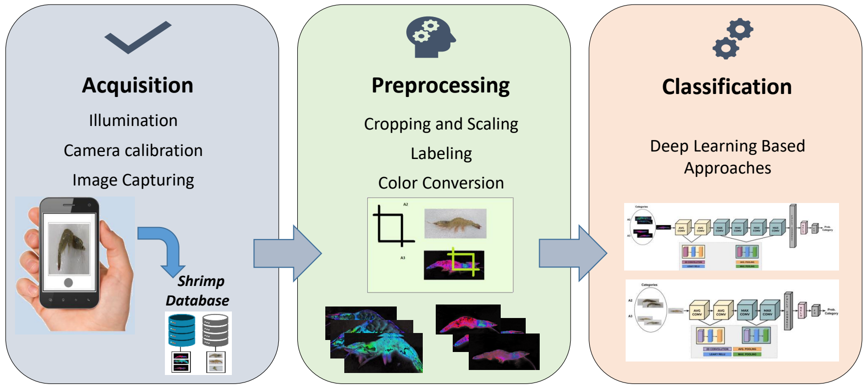

Fig. 1. Pipeline for shrimp classification.

almost 30% larger, we augment the dataset with less samples and undersample the larger class. Another limitation is the similarity that the shrimp samples of categories present to each other. Those limitations can lead to the network failing to learn in its early stages and thus minimizing the performance of the resulting trained model. In the architecture, to reduce the problem caused by the discarding of negative information, it is proposed to use the Leaky ReLu activation function, which allows the information to maintain the necessary variability in the outputs of the model layers so that they remain differentiable and the model can continue learning. The main contributions in the paper are summarized as follows:

- A dataset with labeled images have been generated; it contains high-quality data to be used for training deep learning-based approaches. This dataset contains images from different points of view, illumination, and backgrounds. The dataset corresponds to a variety of shrimp species named Penaeus vannamei. This dataset will be available for the computer vision community.
- A lightweight CNN architecture is proposed, to support the automation of the shrimp classification for a massive distribution market. The model is trained using our dataset and it achieves better results compared with other models of state of the art.

The manuscript is organized as follows. Section 2 presents works related to the classification problem, which serve as the baseline to design our image acquisition system, the image preprocessing, and the proposed architecture presented on the pipeline. Section 3 presents the proposed shrimp classification architecture. Experimental results and comparisons with different implementations are given in Section 4. Finally, conclusions are presented in Section 5.

2 Related Work

As described above, this paper presents an approach to perform shrimp classification according to their pigmentation. To define the best architecture design, different approaches have been reviewed in the literature for shrimp classification. Some of these techniques are based on color information, and patterns detected, among others. In this section, some relevant techniques related to this topic have been summarized.

Most of the techniques are based on deep learning, however, some approaches are proposed using classical computer vision techniques or machine learning models. One of the approaches based on machine learning is presented in [8] where the authors propose a method to detect the freshness of shrimp. The method is based on the use of labels that change their color depending on the state of the freshness of the shrimp. The label detects the high content of flavonoids present in shrimp. With the collected information, the authors have implemented an algorithm based on the near neighbors model of machine learning to perform the classification and quantization of the sensed colors. Additionally, another machine learning-based approach was proposed by Carbajal et al. [1], where the authors propose a fuzzy logic inference system based on an abstract to classify shrimps' habitat quality to solve a biological problem.

Another approach based on the use of CNN and logistic regression has been presented in [11]. It uses visible and near-infrared hyperspectral imaging techniques to discriminate the freshness of shrimp while frozen. Shrimps have been classified into two classes according to their freshness grades (fresh and stale). Each grade is defined based on its volatile basic nitrogen level. A similar approach is presented in [12] where the authors propose a hyperspectral imaging algorithm that combines machine and deep learning techniques to extract spectral features. This proposed approach can estimate the total volatile basic nitrogen (TVB-N) existing on Pacific white shrimps'. On the other hand, in [3], a CNN approach called ShrimpNet is proposed to classify six types of shrimp categories. This architecture can perform shrimp recognition to support the sources of animal protein available for human consumption. Instead, for shrimp quality control, in [4] the authors propose a CNN model that detects the presence of soft-shell on the body of shrimp and determines its level of deterioration. The called Deep-ShrimpCL proposed network introduces combined self-learned features in each layer of the model to optimize local receptive fields. Following the line of classification of shrimp characteristics, in Ma et al. [6], the authors have designed a deep learning network. This network allows monitoring the freshness of the shrimp by recognizing the fingerprint of the smell. This model has used the Wide-Slice Residual Network for food Recognition 50 (WISeR50)[7].

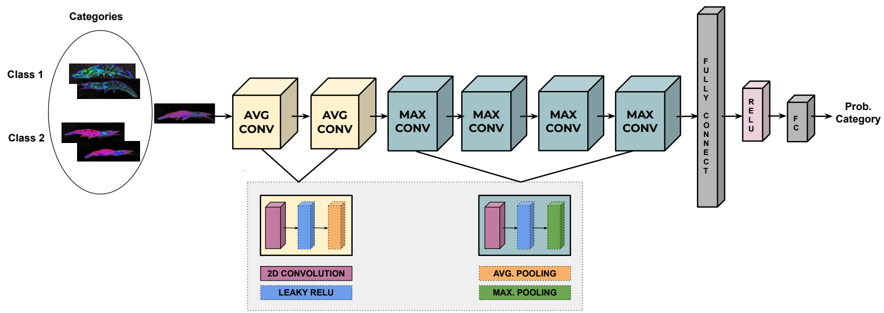

Fig. 2. Shrimp Classification Architecture using HSV dataset

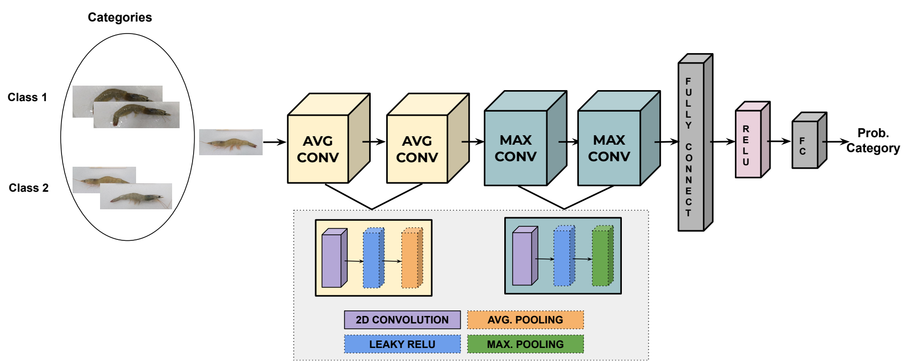

Fig. 3. Shrimp Classification Architecture using RGB dataset

3 Proposed Approach

3.1 Acquisition

To carry out the generation of the dataset, different models of smartphones with different image resolutions, heights and perspectives were used. To facilitate the task of labeling by the experts, physical labels were placed with the name of the category to which each photographed shrimp belonged. Figure 4 shows some examples of the images captured from smartphones. Since the images of each shrimp also contain the category label they belong to, a simple pre-processing has been done to leave only the shrimp in the image and later use these images for training the neural networks. To carry out this task, a script written in Python was used that semi-automatically selects the area where the shrimp is, cuts the image, and saves it in PNG format in a folder where they were organized by category.

Fig. 4. Some illustration of different point of views of the acquired dataset

3.2 Preprocessing

Once the shrimp dataset has been correctly labeled according to its pigmentation categories, it proceeds with the preprocessing before model training. To carry out the classification of shrimp, a set of experiments has been prepared to perform the classification designing a model with a lightweight parameters. Only two of the four categories has been considered in this study, considering the class of shrimp required by the market and final product. The data set has a great similarity in its identifying characteristics. Also as mentioned before, our dataset is not balanced, there are more samples in one category than the other category which makes it more difficult to generalize the model. To overcome this limitation we have proposed training not only with RGB color space images, but HSV color spaces. We have included images converted to the HSV color space to improve the extraction of relevant shrimp features and facilitate the classification process. Also we have reduced our dataset samples to balanced both categories, introducing a more challenging problem. Also, we have applied data augmentation to increase the amount of data available for training, to reduce overfitting, and finally for improving the generalization of the model.

3.3 Classification

A novel-lightweight network has been designed to classify shrimp according to their pigmentation. This deep learning based network has been designed to differentiate the pattern of the two categories of shrimp using both color spaces (RGB-HSV). In order to speed up the training time and overcome the unbalanced dataset size we have applied fine tunning by using the weights of deep networks, such as VGG [10] or ResNet [2]. As mentioned above, we have defined the use of the data set in the HSV color space, since during the experiments, training took less time and better classification efficiency metrics were obtained. The proposed networks have fewer parameters compared to state-of-the-art models that use RGB images. The mentioned architectures for both color spaces (RGB, HSV) are shown in Figures 2 and 3, called ShrimpCL.

Both lightweight models receive as input the set of categorized images. The model designed for RGB image classification consists of five layers: four convolutional layers defined with kernels of size 3 and two fully connected layers. For the model with HSV images, it has been built with 7 layers: six convolutional layers defined also with kernel size of 3 and two fully connected layers. Both models use a cross-entropy loss function to measure the performance of the classification model. In addition, the model includes a LeakyRelu activation function after each convolution and a maximum grouping operation of maximum group layer features to summarize the results of the convolution operation. The last two layers are fully connected, the first one receives the output of the last convolutional layer, which allows connecting all the outputs of the convolution operation, as it was done in the multilayer perceptron technique.

For the classification model with RGB images, the first fully connected layer consists of 512 nodes, while for the HSV model it consists of 1024 nodes. The last fully connected layer in both models (RGB and HSV) enables class scoring using the softmax activation function, to obtain the probability distribution corresponding to each class type. The models support multiclass classification, in our case only two classes are needed. If it is required to modify the number of classes, it is only necessary to modify the number of nodes of the last fully connected layer of the proposed models. To extract the pattern ble to differentiate the categories of shrimps', in our architectures, we have applied a large receptive field in each layer and also, we have applied Leaky relu, reducing the slope during training for negative values resulting in the convolutional operations.

ShrimpCL networks for each color space have been trained from scratch using the Nesterov ADAM (NADAM) optimizer with a learning rate of 0.00027, which provides faster model convergence and generalization. The following section shows the results obtained from each of the experiments carried out and the corresponding comparisons are made to validate the efficiency of the designed models and determine which one presents the best results. The obtained results are presented in the next section.

4 Experimental Results

This section presents the obtained results with the classification networks designed to identify two categories of shrimp according to their pigmentation. The architectures have been designed to receive shrimp samples from each category labeled as input based on the color spaces of the images used. These architectures have been evaluated with images of different color spaces, that is, they have been evaluated in two scenarios: *i*) classification problem of two classes of shrimp samples of RGB color space, and *ii*) problem classification of two classes with shrimp samples of the HSV color space. In addition, as previously indicated, two representative state-of-the-art architectures (i.e,, VGG16 [10] and ResNet50 [2]) have been fine-tuned and it has been possible to determine which network obtains the best metrics. The results obtained are used to make the corresponding quantitative comparisons.

The two-class classification approach was trained using a set of 1,300 images (800 images for training, 300 images for testing, and 200 images to validate the trained model).

It is important to mention that in order to select the best architecture, not only the quantitative values of efficiency for each category of shrimp have been considered, but also the average efficiency of the model and the number of parameters of the proposed architecture. As mentioned above, according to the obtained results, the model proposed for the images of the HSV color space is the one that has obtained the best quantitative metrics. In particular, the values are higher for the case of one of the classes (Class 1) and remain the same in the other class (Class 2), when compared to the model evaluated with images of the RGB color space.

The proposed architecture using HSV images is lighter than the shrimp classification architecture using RGB images. Since this model has fewer parameters, it is trained in less time, without affecting the efficiency of the classification. The results of the proposed lightweight network, ShrimpCL for HSV images, can be seen in Table 1, for the two-class classification problem. The table also shows, the results of the first classification model using RGB images designed for the experiments, but later improved with a lighter architecture. Also, include the state-of-the-art models, such as VGG-16 [10], ResNet-50 [2] and ShrimpCL for RGB images evaluated in this paper. As can be seen, the proposed lightweight architecture using the HSV color space images shows better quantitative results than all previous approaches. Furthermore, it should be noted that the proposed HSV architecture requires fewer parameters than our approach using the RGB color space and more than two hundred times fewer parameters than the VGG architecture.

Table 1. Results of shrimp classification

Network Architecture	Categories		Metrics	
	Class 1	Class 2	Avg. Acc	# of Net. Param.
VGG16-RGB	0.960	0.968	0.964	134268 K
RESNET50-RGB	0.890	0.946	0.918	23591 K
ShrimpCL for RGB	0.963	0.950	0.956	1646 K
ShrimpCL for RGB-Ligth-Weight	0.972	0.965	0.968	593 K
ShrimpCL for HSV-Light-Weight	**0.981**	**0.973**	**0.977**	**473 K**

5 Conclusions

This work tackles the challenging problem of classifying shrimp based on their pigmentation. Taking into account that the pigmentation characteristics between the defined classes are similar in some cases of the samples of the data set, as well as the number of samples for each class, it is not necessarily balanced, which complicates the design of the proposed solution. This lightweight CNN classification model has been validated using shrimp images in the HSV color space. The results prove that using this color space reduces the complexity of the problem. This is because the characteristics detected in the images become more distinguishable. Therefore, the efficiency in the classification of shrimp based on their pigmentation is improved. Model validation could be extended with other shrimp categories and explore the use of other color spaces or spectra to identify patterns presented in the shrimp images.

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