Supervised computer vision system for weight group classification of fingerlings

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***Abstract*—Classifying weight ranges is essential in fish farms since they are sold according to the fingerlings' minimum size, uniformity, and maximum size. Therefore, evaluating the batches' quality is fundamental, which analyzes the growth rate, feed conversion, and survival rate, among others. This paper aims to classify weight ranges for fingerlings of Pintado Real using supervised learning techniques. For this purpose, 60 images were captured, containing a 10-cent Real coin and a ruler next to each fingerling. The software was designed to extract attributes from the images and then serve as inputs for Weka's training algorithms. The J48 algorithm obtained a performance 76.66% in the accuracy metric, and the ANOVA shows no statistical difference. This result is promising since the dataset of images taken from varying distances is a situation that is often common in this type of collection, and the proposed software takes care of standardizing the scale.**

***Index Terms*—weight range classification, image processing, smart fish farm, *Pseudoplatystoma corruscans*.**

I. Introduction

The consumption of animal protein has increased in the last decades, mainly due to the fast growth of the world population, the increase in the purchasing power of families due to the improvement in income distribution, and the more significant occupation of cities by families from the countryside [1].

Aquaculture grows at an accelerated rate annually, exceeding 177 million tonnes in 2019 [2], revealing itself as one of the solutions to meet this high demand for animal protein, with the prospect of exceeding total fisheries not only for human consumption worldwide in 2020 and maintaining growth until 2026 [3]. On the other hand, extractive fishing has decreased annually and is responsible for 40% of the world's fish production. In addition to being unable to supply this demand increase, it causes a tremendous environmental impact on the ecosystem [2].

Despite its rapid and timely development, aquaculture brings few technological advances in managing and breeding larvae, fingerlings, and fish [4]. Fishery helps to maximize the creation of species, which contributes to implementing actions that enhance survival and growth, including new species. In its management practices, classification by size is widespread since it minimizes growth variability, helping to compose groups of fish that reach weight or size more quickly.

The Inovisão (Group for Research, Development, and Innovation in Computer Vision) research group has developed research in partnership with the Pacu Project since 2015, with projects in the area of aquaculture such as the fingerling counter [5]. The Pacu Project is located on the farm Santa Rosa, municipality of Terenos, Mato Grosso do Sul, Brazil, and is responsible for handling genetic improvement resulting in the hybrid species pintado real variant of pintado *Pseudoplatystoma corruscans* Brazilian native species. Therefore, fingerlings production emerges as an activity of economic interest since it is responsible for supplying much of the production of fingerlings in the region, with production in 2021 of more than 52 million fingerlings [1].

The adoption of new technologies in aquaculture, in general, is a complex process because it involves several political, economic, and social factors, such as greater efficiency in the use of resources, the contribution of economic and social policies, technological assistance, and infrastructure [6]. Although Brazil has a coastline and natural resources that favor aquaculture [7], the process of technological development of aquaculture faces basic restrictions and challenges such as reducing corruption, controlling inflation, job creation, etc. so that the country can have its currency valued and acquire international credibility and leverage technological investments in agribusiness [8].

In this context, technological innovations corroborate to

[1]https://cidades.ibge.gov.br/brasil/ms/pesquisa/18/16459

increase the productivity and profitability of the fish farmer since manually executed operations such as fingerling counting and weighing methods are subject to human failures and errors [9] and may also compromise the quality of the product delivered due to physical damage they are subject.

Thus, technological innovations from various areas of knowledge, especially automation, robotics, the Internet of things, cloud computing, big data, and communication infrastructure, among others, are increasingly deployed in fish farms to increase production, reduce losses, ensure environmental sustainability and improve process control [10]–[13]. The advent of computer vision and artificial intelligence has increased researchers' and companies' commitment to add technology in this means of production and collaborate in this process of Smart Fish Farm.

This paper aims to use supervised machine learning to explore an approach to classify the weight ranges of these fingerlings commonly used by traditional fish farms.

II. Related Work

To detect and classify over 1000 photographs of 25 different fish species with 81.1% accuracy, Hsiao et al. [14] used a combination of Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) to extract characteristics and a sparse representation-based classifier.

Huang et al. [15] suggested a hierarchical classification system for multi-class classification based on fish color and texture information using the Support Vector Machine (SVM) to achieve 74.8% accuracy in classifying fish species.

An approach using Effective Match Kernels (EMK) and Kernel Descriptors (KDES) was used by Palazzo and Murabito [16] to identify ten fish species in underwater images, achieving 84.4% classification accuracy on a dataset of 50,000 images.

A computer vision system for classifying fish species based on visual characteristics of color, body shape, head shape, and fin rays for six different species was developed by Shah et al. [17], using Convolutional Neural Network-CNN. Another method based on CNN to classify species, family, and taxonomic order of 68 freshwater fish, obtaining accuracy of 87.3%, 93.8%, and 96%, respectively, was developed by Santos and Gonçalves [18].

The identification and classification of underwater fish using cross-convolutional layer pooling on a pre-trained Convolutional Neural Network (CNN) have been proposed by [19]. For a dataset of 27,370 fish images, an accuracy of 98.03% was obtained for the validation set.

An application for classifying 28 species of freshwater fish using five different techniques: HSV and RGB color histograms, Bag of Visual Words, Bag of Features and Colors, Bag of Colors (BoC), and Bag of Colored Words (BoCW) [20]. The best result of the f-measure was obtained by the HSV Color Histogram (94.1%), RGB Color Histogram (92.6%), and BoC (92.3%) learning algorithms.

A hybrid method of optical flow and Gaussian mixture models with YOLO deep neural network was suggested by Jalal et al. [21]. So, YOLO-based object detection systems were used to capture only static and identifiable fish specimens. Gaussian mixture models combined with the optical flow were used to detect freely moving fishies. An accuracy of 91.64% and 79.8% was obtained for the classification of fish species on two different datasets.

In another research, the creation of a non-intrusive machine learning system was described to identify and classify four carp species based on the extraction of visual characteristics of color and texture [22]. The model was based on deep learning in which a 51% data increase was applied for the dataset and 5-fold cross-validation for CNN training and test sets with VGG16 architecture, making it possible to reach 100% accuracy in classification.

Taheri-Garavand et al. [23], CNN used VGG16 architecture to extract characteristics from the images automatically, and subsequently, a network composed of five blocks with different convolution cores to classify the degree of carp freshness to monitor the quality of the product, in which it was obtained a classification accuracy of 98.21% for the proposed model.

This document differs from the works mentioned above in the following aspects:

1) The challenge of the article was to explore classification based on photos taken on a variable scale, which the software transforms into the real scale.
2) Stratification based on fingerling's weight ranges has yet to be explored in the literature for classification problems.
3) The software and dataset can be made available for use, including for improvement.
4) The ARFF format generated can be used in other software and proprietary tools.

III. Materials and methods

The experiments were carried out through a dataset with 60 images, each one containing a Pintado Real fingerling, a 10 cent of the Real coin, and a ruler, objects used as calibrators since the distance from the camera to the fingerling in this image dataset, is not fixed.

The images were captured by an iPhone 6, in the camera's standard configuration and with focus adjusted manually. The fingerling was individually weighed in the university laboratories immediately after capturing each image, using an SSR-600 Class II scale.

Each image has its label and the weight (biomass) of the respective fingerling, which varies between 2.98 and 16.72 grams. Named ALEV60P [24], this image dataset is available on the INOVISAO[2] group research group's website. Figure 1 shows an example of the mentioned image dataset.

Python software was developed to extract the area and perimeter attributes of the fingerlings. The computer vision library, OpenCV, specifically segmentation techniques using thresholding and contour detection, was used. The software outputs an ARFF file, the data input format of Weka, the

[2]https://www.kaggle.com/datasets/marciopache/alev60p/

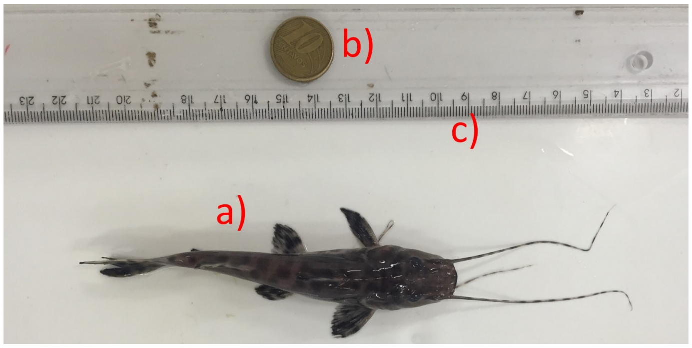


Fig. 1. Example of the ALEV60P image dataset containing a fingerling (a), coin (b) and ruler (c).

software used to train machine learning algorithms. Figure 2 shows the graphical interface of the software developed using the Tkinter library.

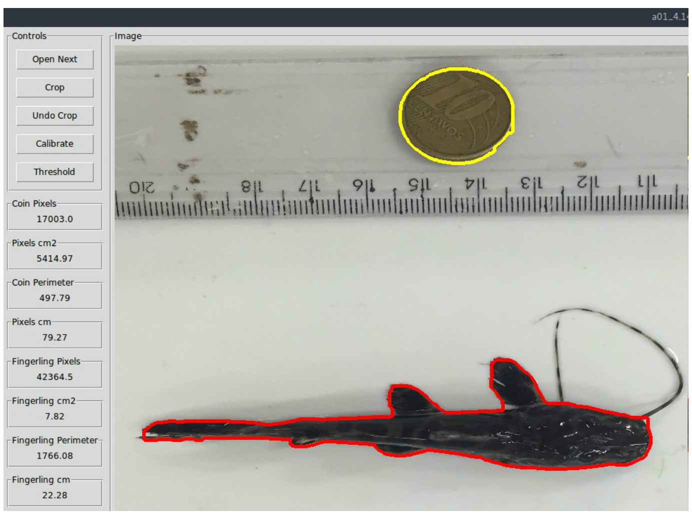


Fig. 2. Software interface responsible for extracting the fingerling area and perimeter attributes.

Figure 3 shows the step-by-step operations for extracting the measurements of the fish fingerlings and calculating the area. After opening the image, we need to reference something to remove the picture's scale, so we use a 10-cent Real coin. The software converts the RGB image to grayscale, uses a Gaussian Blur filter to smooth the colors with neighboring pixels, and performs the morphological operations of opening and closing. At the end of the process, we extract the contours, for which the algorithm searches the image for the coin to calculate the scale, and finally calculates the area of the fingerling and draws the outline to be shown in the software interface.

The software outputs were submitted as input to machine learning algorithms on Weka data mining Waikato software. Figure 4 shows the utilization process of these tools.

After pre-processing and extracting measurements, the images were labeled according to the weight (biomass) measured. In this way, three classes were created containing the same number of images, i.e., 20 for each category, totaling 60

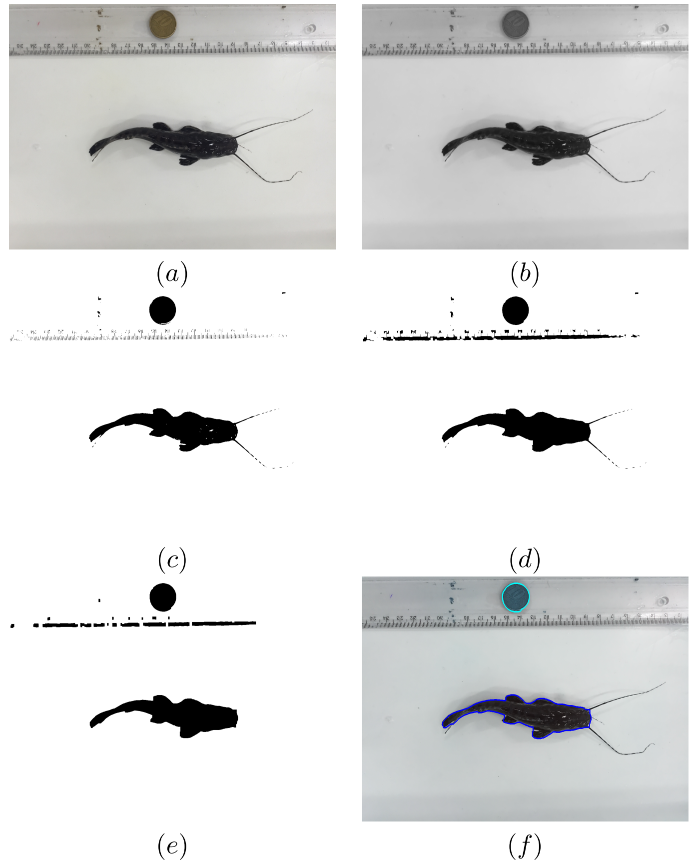


Fig. 3. The step-by-step image transformation for the fingerling measurements extraction: In the first step, it adds (a) Real RGB Image, the algorithm transforms the (b) image into gray and Gaussian Blur operation, next it performs the (c) binarization of the image, performs the morphological operations (d) opening and (e) closing. The last step extracts the coin averages to find out the scale of the image, and (f) draws the contours of the coin and the fingerling.

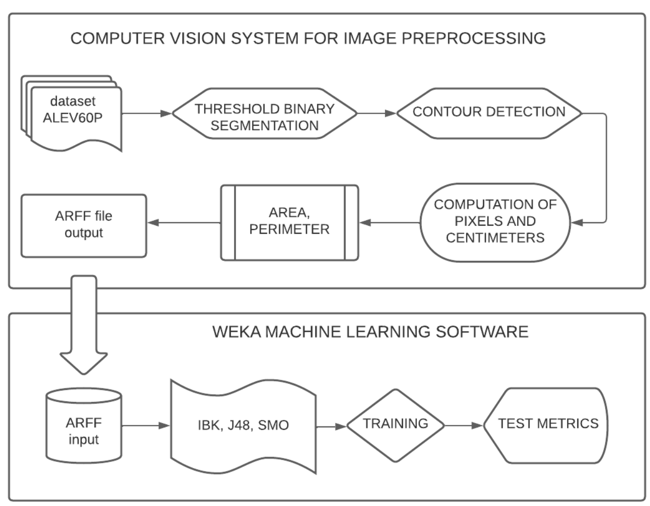


Fig. 4. Software usage flowchart.

images of Pintado Real fingerlings. The classes were made according to the purpose of the marketing management, as follows: Underweight range: In this case, the batch needs more attention, as it will need more feed and medication. Normal range: in line with the expected feed conversion chart; and Overweight range: selection of matrices for larviculture.

The following classification techniques were used: Instance-based (IBK), with k = 3, C4.5 Decision Tree (J48), and Sequential Minimum Optimization (SMO) with the 10-fold cross-validation, as indicated in the work of [25].

- IBK: K-nearest neighbors is an instance-based classifier. The value of k=3 was set so that the three nearest neighbors were evaluated during the classification process. The lowest Euclidean distance value is used as the classification criterion. For more information, see [26].
- J48: It is a widespread implementation of the decision tree based on the C4.5 algorithm. It recursively creates data partitions based on the values of the input attributes presented. For more information, see [27].
- SMO: Uses John Platt's sequential minimum optimization approach to put his support vector classifier training algorithm into practice. For more information, see [28]–[30]

The metrics evaluated in addition to accuracy were Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Kappa value, Area Under the Curve (ROC), Precision, Revocation, and F-Measure.

The analysis of variance (ANOVA) test was performed, considering the significance level of 5%. For this hypothesis test, the accuracy values for the cross-validation of 10 folds were used, giving 30 observations and two variables (accuracy and algorithm). This test was carried out in R-studio in conjunction with the R software.

TABLE I
PERFORMANCE METRICS RESULTS USED TO EVALUATE THE PROPOSED COMPUTER VISION SYSTEM

Metrics	Algorithms		
	IBK	SMO	J48
Accuracy (%)	68.33 (±)	73.33 (±)	76.66 (±)
Kappa statistic	0.525	0.6	0.65
MAE	0.244	0.296	0.222
RMSE	0.406	0.385	0.372
Precision	0.674	0.735	0.764
Recall	0.683	0.733	0.767
F-Measure	0.677	0.73	0.759
ROC Area	0.807	0.823	0.796

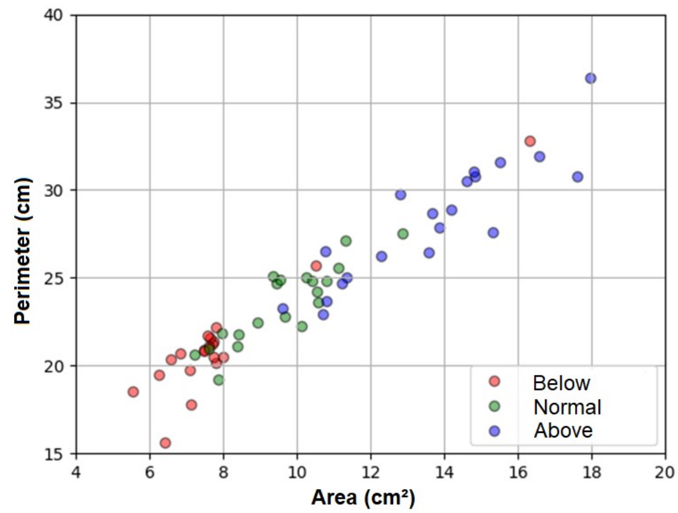


Fig. 5. The distribution of weights in the Below, Normal, and Above classes correlated with perimeter and area.

IV. RESULTS AND DISCUSSION

Table I presents the performance metrics results to evaluate the proposed computer vision system. The metrics were compared for three algorithms tested. The J48 classifier obtained the highest accuracy of 76.66%, corroborated by the kappa metric of 0.65 used to compare predicted Accuracy with actual Accuracy. The lowest MAE and MSE errors were also for the J48, with values of 0.222 and 0.372, respectively. J48 also obtained better Precision, Revocation, and F-Measure metrics results. Although the IBK and SMO techniques obtained inferior results, SMO got an ROC curve area of 0.823, higher than the others.

Figure 5 shows the distribution of the weights correlated with the area and perimeter attributes for the 60 fingerlings in the dataset. As we can see, some samples from different classes are mixed, especially if we compare the Normal type with the others. We can see an atypical sample, an outlier, which belongs to the underweight class and is very far from the other samples in the same category. An error in weight measurement or image labeling may have caused this atypical sample.

Figure 6 shows the boxplot of the techniques' accuracy metric considering all cross-validation folds. So, in the J48 algorithm, the median is 75%, and the interquartile range ranges from 68% to 82% with a maximum value of 100%. SMO and IBK have the same median value of 66.67%. Therefore, the SMO algorithm's minimum value is close to 33%, i.e., from the minimum to the lower quartile. IBK had the worst performance of the algorithms with three outliers.

The confusion matrix in Figure 7 presents the result of the machine learning algorithms. The main diagonal gives the correct classifications of the items, and the numbers outside the main diagonal give the incorrect model classifications. When analyzing the relationship between the classes, we see that the errors are concentrated on the border between Below for Normal and Normal for Above. This problem may be caused by the number of fingerling samples with similar attributes and different weights, possibly related to the fingerling area's segmentation in the image, which may cause an incorrect classification due to mass density.

Note that in all the confusion matrices, there is only one error between the Below and Above classes: a prediction of

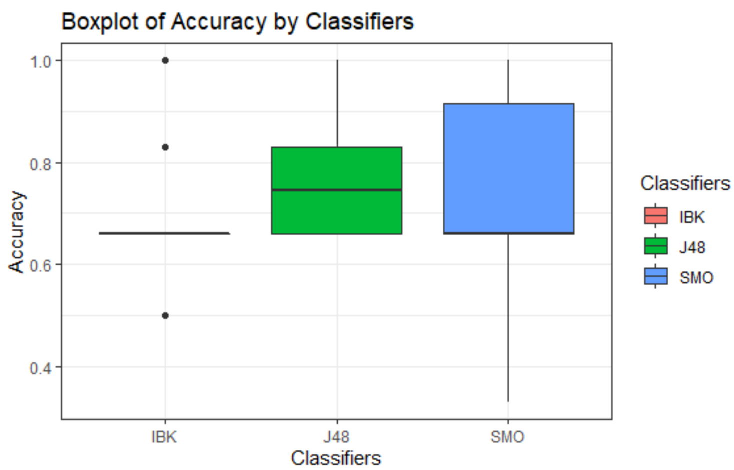
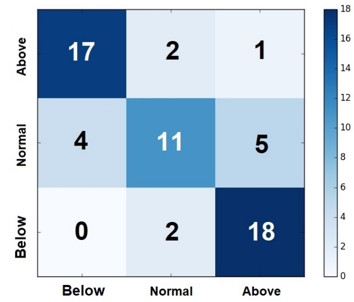


Fig. 6. Box plot comparing the performance of classifiers for accuracy metric.

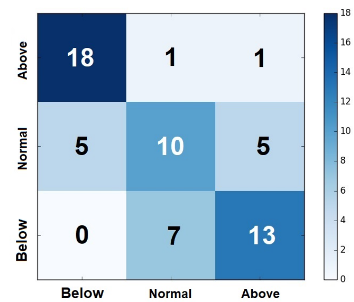
above overweight when the sample is an underweight fingerling. On the other hand, considering the test set evaluated, there was no prediction error for the Underweight class.

The results of the ANOVA test using the technique and accuracy as variables are presented. Compared with the classification modeling, the approaches consider the p-value, the statistical value that must be compared with the referential probability value. In this case, the p = 0.82295 value, the probability is considered to be 0.8%, which is impossible to discard the null hypothesis since it is impossible to affirm they have statistical significance because the p-value is higher than 0.05.

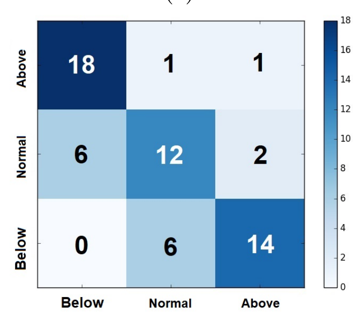
The result showed that looking at the median between the compared techniques, the J48 showed more consistency in the classification process since its average is the highest among the methods. This means that most classifications using cross-validation obtained accuracy in most folds above 66%.



(a)



(b)



(c)

Fig. 7. Confusion Matrix for J48 (a), IBK (b), and SMO (c).

V. Conclusion

This paper explored the weight range classification problem commonly used to separate fingerlings in fish farms. Despite the SMO technique being the most accurate in the experiments, the J48 has had a better median among the four tested algorithms. During the investigation, several gaps were found, in which we identified that some samples had attributes with close values but different weights, thus providing incorrect classifications. However, the results were promising because, in most cases, the classifications were correct, showing a correlation between area and perimeter. There are several possibilities for future approaches: I - extract more characteristics besides area and perimeter. II - Create a dataset with more images of several specimens. III - Perform experiments with different cameras that have better resolution. IV - Use deep learning techniques with different architectures aiming for better results than those obtained. V - Apply the techniques to fingerlings of other species. VI - Developing an application for real-time operation with the smartphone's camera is quite a challenge. VII - To create an embedded system, project a gadget using NVidea Jetson or another controller device.

VI. Acknowledgments

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