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Research Article

Deep learning-based classification of species in central-southern fisheries in Chile

Eloy Alvarado[1], Francisco Plaza-Vega[2], Carlos Montenegro[3] & Oscar Saavedra[1]
[1]Departamento de Industrias, Universidad Técnica Federico Santa María, Santiago, Chile
[2]Universidad de Santiago de Chile, Santiago, Chile
[3]Instituto de Fomento Pesquero, Valparaíso, Chile
Corresponding author: Francisco Plaza-Vega (francisco.plaza.v@usach.cl)

ABSTRACT. This study introduces a novel deep learning methodology for identifying fish species in central-southern Chile's pelagic and demersal fisheries. Using a dataset of 8,118 high-resolution images encompassing 18 species, two Convolutional Neural Networks (CNNs) were developed: a custom-designed CNN, which achieved an overall accuracy of 86% (95% CI: [0.8355; 0.8826]), and an adapted VGG16 model, which reached 95% (95% CI: [0.9355; 0.9651]) when tested on the same set of 811 images. While both models perform strongly, challenges persist for specific species, particularly *Brama australis* and *Strangomera bentincki*, with 33 and 53% classification rates in the VGG16 model, highlighting opportunities for dataset enrichment and algorithmic refinements. Additionally, Gradient-weighted Class Activation Mapping (Grad-CAM) was employed to visually interpret the decision-making process of the CNN, providing insight into the regions of the image most relevant to classification. Developed using the Keras API and TensorFlow framework within the R programming environment, our approach underscores the importance of advanced computational tools in enhancing species classification. The results lay the groundwork for future expansions into comprehensive frameworks utilizing computer vision to recognize fish species on board, quantify catches, and detect discards and bycatch. These advancements could significantly benefit Fisheries Observer programs, enhancing enforcement and aiding sustainable fisheries management. Ultimately, this work promotes efficiency and efficacy in monitoring, fostering a sustainable future for marine biodiversity in Chile and potentially other regions and wider marine ecosystems.

Keywords: species recognition; deep learning; bycatch; fish management; Convolutional Neural Networks

INTRODUCTION

Bycatch-the unintentional catch of non-target species within fishing operations-remains a critical issue in marine conservation and sustainability due to its capacity to degrade marine ecosystems (Kelleher 2005, Soykan et al. 2008, Davies et al. 2009, Komoroske & Lewison 2015). Discards, a subset of bycatch, refer to the fraction of the overall catch thrown back into the sea (Kelleher 2005). Because discarding can be a wasteful practice and conflict with sustainable fishing objectives, the FAO Code of Conduct for Responsible Fisheries (FAO 1995) has articulated guiding principles and international standards to address its impacts. These include: i) considering discard impacts when applying precautionary approaches to fisheries management; ii) systematically collecting and reporting discard-related information; iii) collecting high-quality ecosystem and fisheries data to assess discard status; iv) promoting technological and operational methods to minimize discards; and v) implementing observer and inspection programs to foster compliance with management measures.

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In Chile, fishing activities contribute nearly 0.7% to the national gross domestic product, with total landings averaging around 2 million tons over the past five years (SUBPESCA 2022). Of this, 60% originate in the central-south region. Pelagic species-such as anchovy (*Engraulis ringens*), common sardine (*Strangomera bentincki*), and jack mackerel (*Trachurus murphyi*) account for roughly 56% of these landings, while demersal species-like common hake (*Merluccius gayi*) and hoki (*Macruronus magellanicus*) contribute about 4%. Under Chile's General Law of Fishing and Aquaculture, discards must be included when determining annual global catch quotas (Paragraph 1 Bis, Law N°20.625), a critical measure to ensure sustainable exploitation of marine resources. Although global bycatch rates have been estimated to reach 40.4% (Davies et al. 2009), discard rates in some Chilean fisheries, such as the southern hake (*Merluccius australis*), were estimated to be around 19% during 2000-2003. To address such challenges, Chile began incorporating bycatch and discard observations into its fisheries monitoring programs in 2014, starting with pelagic and extending to demersal fisheries. By 2017, bycatch and discard reduction plans had been formally integrated into observer and monitoring programs for major fisheries, implemented by the Instituto de Fomento Pesquero (IFOP), involving administrative and conservation measures, the adoption of technologies aimed at reducing discards, robust monitoring programs, the evaluation of effectiveness of these measures, training and awareness initiatives, and a code of best practices (Román et al. 2022, Vega et al. 2022).

Among the technological applications supporting the observation and monitoring of fishing activities, electronic monitoring has emerged as a cost-efficient tool for reducing discards and bycatch (Van Helmond et al. 2020). However, integrating such tools and electronic reporting, methodological, computational, and connectivity advancements presents new challenges. Chief among these is efficiently handling the vast amounts of data generated while transforming it into actionable information and knowledge for fisheries management (Komoroske & Lewison 2015, Bradley et al. 2019, Gilman et al. 2019, 2020). Conventional data analysis methods often prove inadequate for mining all relevant insights from large-scale datasets. Consequently, establishing appropriate protocols and techniques for monitoring and diagnosing catches, discards, and bycatch becomes essential for providing scientific guidance and supporting sustainable management. In this context, emerging deep learning and computer vision techniques offer promising new avenues for automated identification, real-time data processing, and enhanced ecosystem understanding through improved detection of non-target species. These advancements can substantially benefit resource-limited fisheries management strategies by reducing human error, bias, and operational expenses.

Numerous studies have already demonstrated the potential of advanced computer vision methods for automated fish recognition and segmentation. Lu et al. (2020) achieved 96% accuracy using VGG16 to classify tunids, billfishes, and sharks in deck images. Ju & Xue (2020) reported a 97% accuracy with a customized AlexNet (FAN) for fish species. Similarly, Ovalle et al. (2022) used Mask R-CNN segmentation and MobileNet-V1 measurement to achieve an average accuracy of 98% under low overlapping conditions. Dos Santos & Gonçalves (2019) introduced a three-branched Convolutional Neural Networks (CNN) model for 68 fish species, reaching up to 87% accuracy in species-level classification. Villon et al. (2018) and Xu et al. (2021) also documented high accuracies (98% and over 91%, respectively) using CNNs or transfer learning methods. In Japan, Miyazono & Saitoh (2018) employed a transfer learning model based on CIFAR-10 and AlexNet for 50 species, with 71 to 91% accuracy.

Building on these developments, this article proposes an automated deep-learning approach for fish species identification in Chile's central-south pelagic and demersal fisheries. In particular, 18 fish species are classified from self-collected images using CNNs. The objective is to establish a robust methodology demonstrating how these computational methods can advance fisheries management, laying the foundation for a more comprehensive framework. Such a framework would recognize fish species on board and aid in quantifying catches and monitoring discards and bycatch. This integrated system is expected to bolster the effectiveness of Fisheries Observer programs, enhance compliance, and promote sustainable resource use across Chilean fisheries and wider marine ecosystems. Ultimately, the approach aims to improve the estimation of bycatch and discards through real-time detection and quantification, thus supporting more informed mitigation strategies and policy decisions. All code developed in this study is available in our GitHub repository (Alvarado & Plaza-Vega 2023), provided as supplementary material.

MATERIALS AND METHODS

Data

In this research, we utilized a comprehensive dataset composed of 8,118 high-resolution images (each with dimensions of 1,200×800 pixels), featuring 18 species from the central-southern regions of Chile that are objective and non-objetive fisheries (i.e. accompanying fauna), bycatch, and discard species are considered from both pelagic and demersal fisheries. These images were meticulously categorized by expert scientific observers, playing a pivotal role in the continuous monitoring activities within the fisheries sector. For detailed information on the specific species included in this research and the number of images corresponding to each species, please refer to Table 1.

The dataset is characterized by its diversity in background settings and illumination conditions, as illustrated in Figure 1. This study encompasses self-collected images acquired as part of an initiative to advance technological advancement in the monitoring programs of pelagic and demersal fisheries conducted by the IFOP between March 2020 and October 2022.

To optimize the 8,118 images for model development, the dataset was partitioned into training, validation, and testing subsets according to a 70-20-10 ratio. Owing to the limited availability of images for certain species, -*Brama australis*, in particular (Table 1)-data augmentation techniques (Shorten & Khoshgoftaar 2019) were applied to enhance model generalization and mitigate overfitting. Specifically, the following transformations were incorporated:

- Flipping (horizontal/vertical): random flips simulated the specimens' varying orientations, accounting for different capture angles and handling positions.
- Rotation: images were rotated within a predefined angle range (±15°) to replicate natural inclinations typically observed in field scenarios.
- Shifting: minor horizontal and vertical shifts (up to 10% of the image dimensions) addressed off-center captures commonly occurring during photographic collection.
- Shearing: a moderate 0.2 shearing factor introduced slight skewing, accommodating variations in camera angles.
- Zooming: Small zoom factors (10-20%) reproduced conditions where specimens appear at different scales within the frame.

These transformations effectively expanded and diversified the training subset, enhancing the model's robustness to the inherent variability of fisheries data.

Table 1. Species included in the study, with their respective number of images available.

Species	Number of images
Brama australis	30
Cilus gilberti	600
Engraulis ringens	343
Genypterus chilensis	99
Merluccius gayi gayi	281
Scomber japonicus	247
Strangomera bentincki	186
Stromateus stellatus	172
Thyrsites atun	1539
Trachurus murphyi	914
Epigonus crassicadus	454
Seriorella punctata	313
Genypterus maculatus	181
Paralichtys microps	389
Apristurus nasutus	592
Caelorinchus fasciatus	826
Eleginops maclovinus	662
Bovichtus chilensis	290
Total	8,118

To balance computational efficiency with image clarity, each image was resized from 1,200×800 to 500×500 pixels, ensuring sufficient resolution for reliable species identification without unduly increasing computational overhead.

Methodology

Our methodology employs two distinct CNNs (Goodfellow et al. 2016), implemented via the *Keras* API (Chollet et al. 2015) with a TensorFlow (Abadi et al. 2015) back end, all within the R language environment (R Core Team 2022). Leveraging the computational power of an NVIDIA GeForce RTX 4080 GPU, both models were executed in GPU mode, substantially curtailing the necessary training and testing processing times, thus enhancing the efficiency and feasibility of our approach.

Customized Convolutional Neural Network (CNN)

A customized CNN was designed to identify morphological features in fish species images from central-southern Chilean fisheries. The model (Fig. 2), consists of convolutional layers with 32, 64, 64, 128, and 128 filters, alternated with max-pooling layers, extracting hierarchical features from the images while improving computational efficiency through spatial dimension reduction. Utilizing the rectified linear unit (ReLU) activation function, the model navigates non-linear feature spaces, learning complex patterns from the data. During training, categorical crossentropy and

Figure 1. Examples of images included in this study, with their respective scientific names.

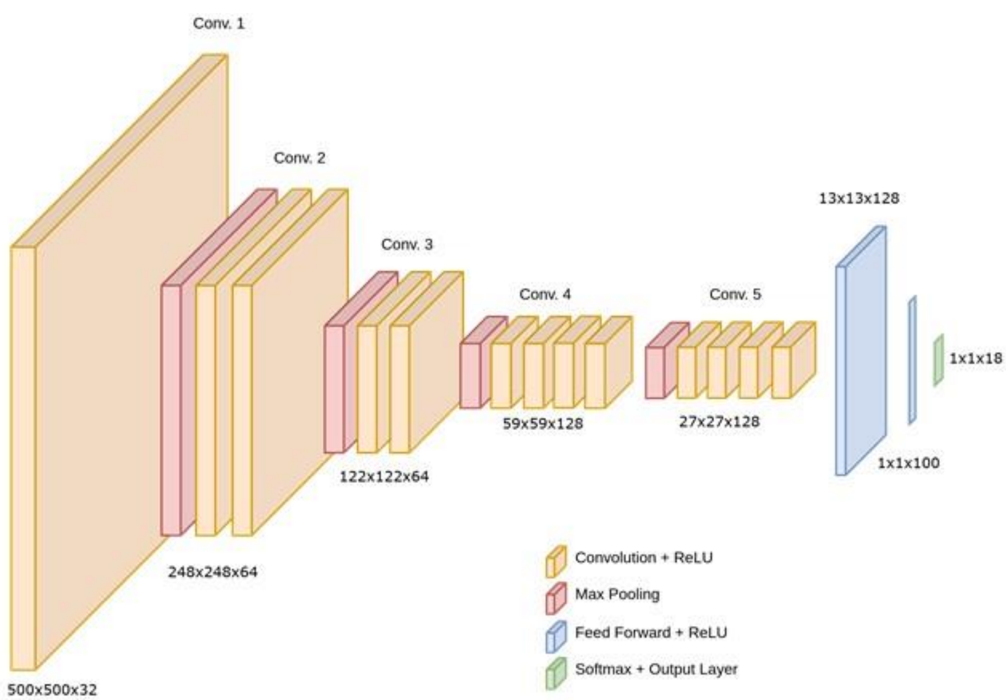

Figure 2. Custom Convolutional Neural Network architecture. ReLU: rectified linear unit.

the RMSprop optimizer (Tieleman 2012) (with a learning rate of 10-4) were employed to balance convergence speed and stability. Validation, employing augmented images, ensured model generalization and mitigated overfitting. The final layers use a Softmax activation function, outputting probability distributions across 18 fish species categories. Dropout layers (Srivastava et al. 2014) were incorporated to prevent overfitting, randomly nullifying 25% of neurons during training, enhancing model robustness and predictive capabilities across varied inputs.

Adapted VGG16 Network

The VGG16 model, developed by the Visual Geometry Group at the University of Oxford (Simonyan & Zisserman 2014), was selectively adapted for the specific task of fish species classification in our study. Initially pre-trained on the substantial ImageNet dataset (Russakovsky et al. 2015), we tailored the model to our unique classification context, while specifically focusing our adaptations on its fully-connected top. As depicted in Figure 3, the modifications included the addition of convolutional layers with 64 filters and a 3×3 kernel size, utilizing a ReLU activation function. The implementation of global average pooling followed this, as did the inclusion of dense layers and the application of dropout for regularization. The adaptation culminated in a final dense layer featuring 18 nodes, each representing a fish species, and employed a Softmax activation function to produce probability distributions across the species categories.

RESULTS

Building upon the insights from Alsmadi & Almarashdeh (2022), Barbedo (2022), and Rubbens et al. (2023), and the employment of accuracy as a classification metric is notably prevalent in marine sciences, particularly in image classification applications. This metric's appeal lies in its clear and direct approach to quantifying a model's performance, making it an invaluable marine science tool. In the specific context of fish image classification, where the primary objective is accurately identifying species through visual data, accuracy directly measures a model's effectiveness, reflecting the proportion of correct identifications made.

During the training phase, the custom CNN model demonstrated a training loss near 0.6, with the validation loss slightly lower, which reflects a well-tuned learning process with minimal overfitting, which was further corroborated by the accuracy metrics. Both the training and validation accuracy levels were observed to be above 80%, indicating the model's proficiency in accurately classifying the species, as seen in Figure 4.

In comparison, the VGG16-based pretrained model, adapted to the specificities of the Chilean fish species dataset, showed a refined performance. It registered a training loss of around 0.5 and a notably lower validation loss of approximately 0.4, suggesting a more efficient learning curve and a better generalization capability than the custom CNN model. The accuracy measures were particularly high, with the training and validation accuracy surpassing 80%, as depicted in Figure 4.

The evaluation of the models using confusion matrices is shown (Figs. 5-6). The matrices provide a comprehensive view of the classification performance across the different species in the dataset.

The confusion matrices for the custom CNN model (Fig. 5) and the adapted VGG16 model (Fig. 6) are provided to demonstrate the prediction distributions across various classes. Figure 5 shows the classification matrix for the custom CNN model tested on 811 images spanning 18 species, achieving an overall accuracy of approximately 86% (CI: [0.8355; 0.8826]). This model exhibits strong performance for most species but shows lower predictive accuracy for species like *Brama australis*, *Genypterus maculatus*, *Seriolella punctata*, *Strangomera bentincki*, and *Bovichtus chilensis*, highlighting areas for potential improvement. Conversely, the adapted VGG16 CNN model, as depicted in Figure 6, evaluated on the same test set, demonstrates superior performance with an accuracy rate nearing 95% (CI: [0.9355; 0.9651]). Despite its effectiveness, the adapted VGG16 model faces challenges in accurately classifying certain species, particularly *B. australis* and *S. bentincki*, with 33% and 53% classification rates, respectively, suggesting specific targets for future enhancement.

The performance metrics for the two models are provided in Tables 2 and 3. We observed exceptional sensitivity in both models for species such as *Caelorinchus fasciatus* and *Merluccius gayi gayi*, with the values reaching 1 and 0.966, respectively, in the custom CNN, and 1 for both species in the VGG16 model. Specificity, indicating the accuracy in identifying true negatives, was uniformly high across most species, often reaching the maximum of 1. Precision and Negative Predictive Value (NPV) metrics, assessing the reliability of the classification of the models, were generally high. However, a notable outlier was the precision for *B. australis* in the custom CNN model, which was marked as *NaN* due to a lack of positive predictions. Balanced accuracy, a vital metric in datasets with class imbalances, demonstrated the models' consistent accuracy across various classes, with many species, such as *Thyrsites atun* and *Eleginops maclovinus*, achieving scores close to 0.989 and 0.978 in the custom CNN, and 0.991 and 0.999 in the VGG16 model, respectively.

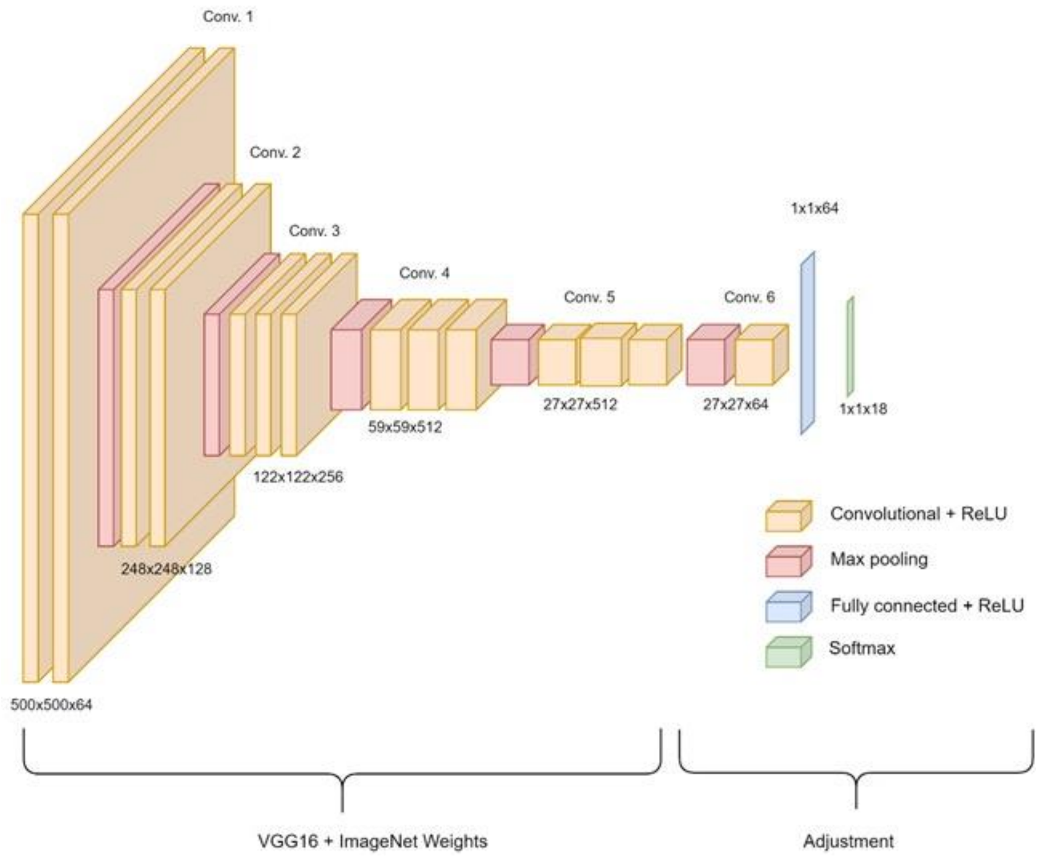

Figure 3. Adapted VGG16 Convolutional Neural Network Architecture. ReLU: rectified linear unit.

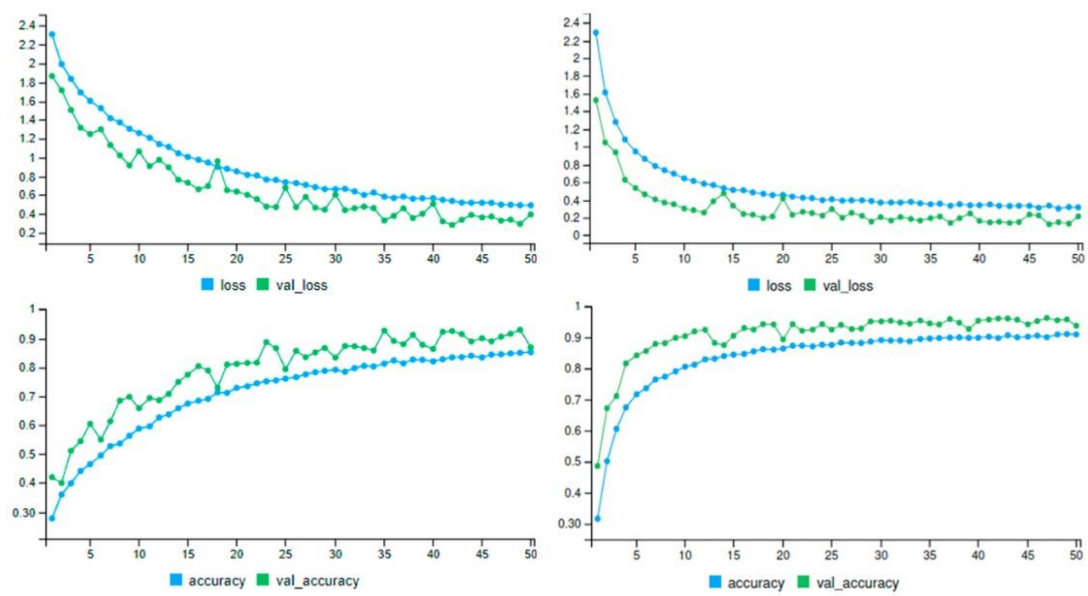

Figure 4. Training performance measures for Convolutional Neural Network (CNN) models, loss and accuracy on the upper and lower sides of the figure, respectively. Custom CNN (on the left) and adapted VGG16 CNN (on the right).

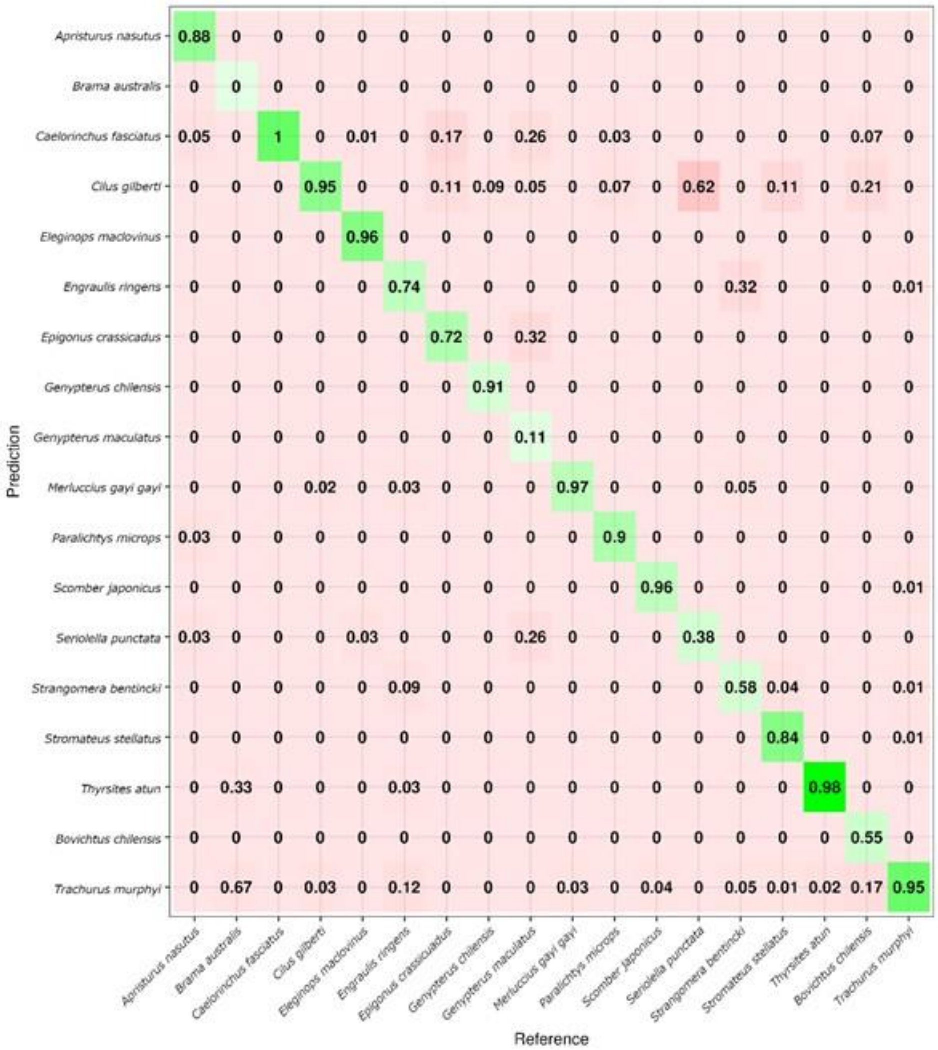

Figure 5. Confusion matrix for custom Convolutional Neural Network based on the testing subset of images.

The heatmap visualization is achieved by overlaying the activation map onto the original image, providing an intuitive graphical representation of model focus. Figure 7 presents Gradient-weighted Class Activation Mapping (Grad-CAM) visualization of randomly selected images from each species included in the study.

We employed Grad-CAM to visually interpret the decision-making process of our CNN. Grad-CAM is a widely acknowledged technique that produces visual explanations for decisions from many CNN-based models, rendering it model-agnostic (Selvaraju et al. 2017).

By utilizing the gradients of the target concept, which flow into the final convolutional layer, Grad-CAM generates a coarse localization map that highlights the important regions in the image for predicting the concept. Specifically, it leverages the spatial information preserved in convolutional layers to understand which parts of the input image are deemed significant by the CNN.

DISCUSSION

This work demonstrates the efficacy of deep learning in classifying 18 fish species relevant to pelagic and demersal fisheries in the central-south region of Chile. To achieve this objective, two CNN models, namely custom CNN and adapted VGG16 CNN, were deployed and evaluated regarding their general classification performance and species-specific identification capabilities. The results indicated commendable performance for both models

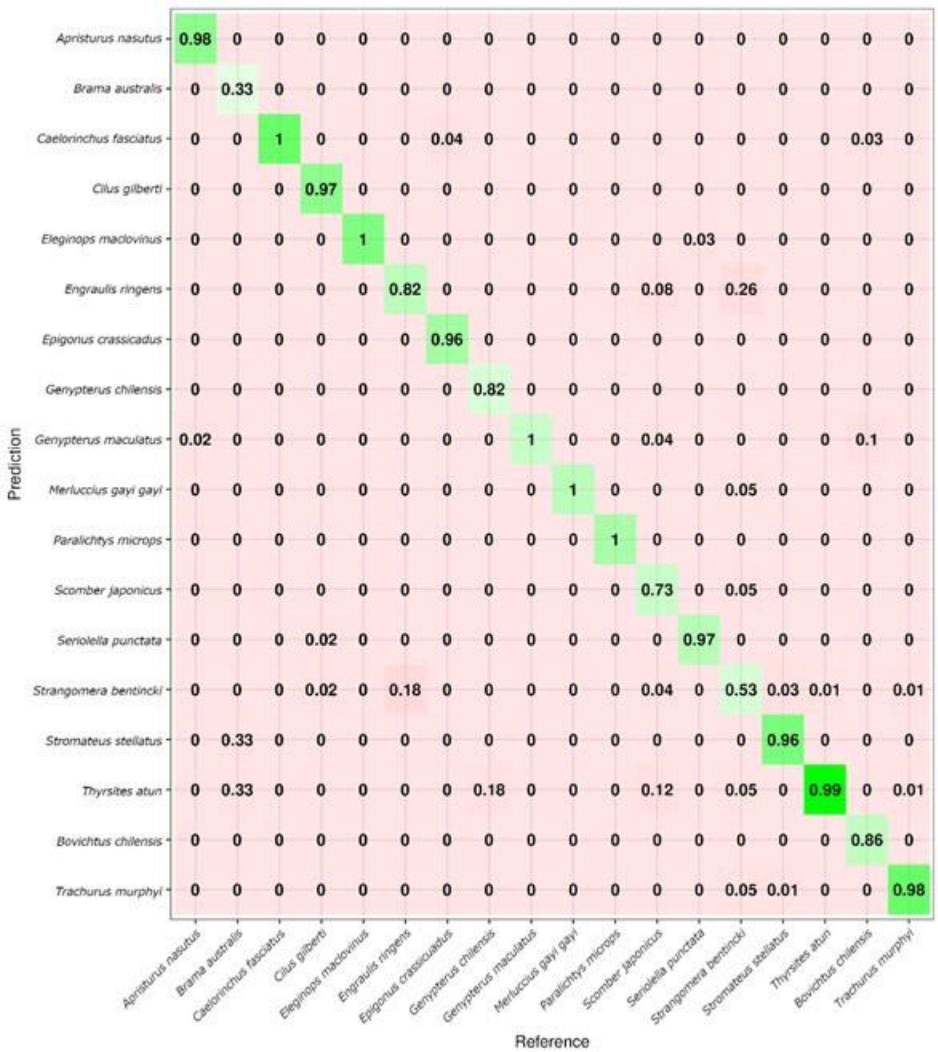

Figure 6. Confusion matrix for adapted VGG16 Convolutional Neural Network based on the testing subset of images.

during the training and testing phases, underscoring the effectiveness of CNN-type models in overall fish species classification. The adapted VGG16 CNN model exhibited significantly superior outcomes to the custom CNN model.

Despite the overall effectiveness of the adapted VGG16 model, certain species remain challenging to classify accurately. In particular, *B. australis* exhibits a low classification rate (33%), largely because it is often misclassified as *Thyrsites atun* or *Stromateus stellatus*. Determining the precise morphological features causing this confusion is difficult due to the limited number of *B. australis* images (30) available for training, which restricts the model's ability to learn distinctive characteristics for this class. *S. bentincki* is frequently misclassified as *E. ringens*, reflecting a broader issue of morphological similarity among small pelagic species that compromises the model's discriminative capacity. These findings underscore the importance of augmenting datasets with a more extensive and diverse range of images, thereby providing CNNs with a wider variety of examples to learn. Since CNNs rely on multi-level feature extraction from pixel data, the availability of richer image repositories is crucial for capturing subtle interspecies variations and improving classification performance across all taxa under investigation (Barbedo 2018, Rekha et al. 2020, Yang et al. 2021, Alsmadi & Almarashdeh 2022).

Recent studies have underscored the efficacy of technologies like Remote Electronic Monitoring (REM) in mitigating bycatch in small-scale fisheries, demonstrating how REM can support observer data, enhance accuracy, monitor the effectiveness of mitiga-

Table 2. Class-specific metrics for the custom Convolutional Neural Network model. NPV: Negative Predictive Value.

Species	Sensitivity	Specificity	Precision	NPV	Prevalence	Detection rate	Detection prevalence	Balanced accuracy
Apristurus nasutus	0.883	1.000	1.000	0.991	0.069	0.061	0.061	0.942
Brama australis	0.000	1.000	NaN	0.997	0.003	0.000	0.000	0.500
Caelorinchus fasciatus	1.000	0.975	0.806	1.000	0.095	0.095	0.118	0.987
Cilus gilberti	0.951	0.946	0.569	0.996	0.070	0.066	0.117	0.948
Eleginops maclovinus	0.955	1.000	1.000	0.996	0.077	0.073	0.073	0.978
Engraulis ringens	0.735	0.992	0.781	0.989	0.039	0.029	0.037	0.863
Epigonus crassicaudus	0.723	0.993	0.850	0.984	0.054	0.039	0.046	0.858
Genypterus chilensis	0.909	1.000	1.000	0.999	0.013	0.011	0.011	0.955
Genypterus maculatus	0.105	1.000	1.000	0.980	0.022	0.002	0.002	0.553
Merluccius gayi gayi	0.966	0.996	0.903	0.999	0.033	0.032	0.036	0.981
Paralichthys microps	0.900	0.998	0.947	0.995	0.046	0.041	0.044	0.949
Scomber japonicus	0.962	0.999	0.962	0.999	0.030	0.029	0.030	0.980
Seriolella punctata	0.375	0.989	0.571	0.977	0.037	0.014	0.024	0.682
Strangomera bentincki	0.579	0.992	0.611	0.991	0.022	0.013	0.021	0.785
Stromateus stellatus	0.838	0.999	0.984	0.985	0.085	0.071	0.072	0.918
Thyrsites atun	0.980	0.997	0.987	0.996	0.175	0.172	0.174	0.989
Bovichtus chilensis	0.552	1.000	1.000	0.985	0.033	0.018	0.018	0.776
Trachurus murphyi	0.953	0.975	0.804	0.995	0.099	0.094	0.117	0.964

Table 3. Class-specific metrics for the adapted VGG16 Convolutional Neural Network model. NPV: Negative Predictive Value.

Species	Sensitivity	Specificity	Precision	NPV	Prevalence	Detection rate	Detection prevalence	Balanced accuracy
Apristurus nasutus	0.983	1.000	1.000	0.999	0.069	0.068	0.068	0.992
Brama australis	0.333	1.000	1.000	0.998	0.003	0.001	0.001	0.667
Caelorinchus fasciatus	1.000	0.996	0.965	1.000	0.095	0.095	0.099	0.998
Cilus gilberti	0.967	1.000	1.000	0.998	0.070	0.068	0.068	0.984
Eleginops maclovinus	1.000	0.999	0.985	1.000	0.077	0.077	0.078	0.999
Engraulis ringens	0.824	0.992	0.800	0.993	0.039	0.032	0.040	0.908
Epigonus crassicaudus	0.957	1.000	1.000	0.998	0.054	0.052	0.052	0.979
Genypterus chilensis	0.818	1.000	1.000	0.998	0.013	0.011	0.011	0.909
Genypterus maculatus	1.000	0.994	0.792	1.000	0.022	0.022	0.027	0.997
Merluccius gayi gayi	1.000	0.999	0.967	1.000	0.033	0.033	0.034	0.999
Paralichthys microps	1.000	1.000	1.000	1.000	0.046	0.046	0.046	1.000
Scomber japonicus	0.731	0.999	0.950	0.992	0.030	0.022	0.023	0.865
Seriolella punctata	0.969	0.999	0.969	0.999	0.037	0.036	0.037	0.984
Strangomera bentincki	0.526	0.986	0.455	0.989	0.022	0.012	0.025	0.756
Stromateus stellatus	0.959	0.999	0.986	0.996	0.085	0.081	0.082	0.979
Thyrsites atun	0.994	0.989	0.950	0.999	0.175	0.174	0.183	0.991
Bovichtus chilensis	0.862	1.000	1.000	0.995	0.033	0.029	0.029	0.931
Trachurus murphyi	0.977	0.997	0.977	0.997	0.099	0.096	0.099	0.987

tion technologies, and guarantee enforcement; this offers a strategic avenue to oversee and curb illegal fishing practices (Worm et al. 2013, Van Helmond et al. 2015, Bartholomew et al. 2018, Glemare et al. 2020, Brown et al. 2021). On that note, advancements in technology, particularly in image recognition, are progressively enhancing the monitoring capabilities of exploitative activities in fisheries. Coupled with decreased data storage costs, these advancements position electronic monitoring as a cost-effective adjunct to fisheries observer programs, promising a substantial shift in operational dynamics.

Barbedo (2022) delineates four pivotal activities in fisheries monitoring: recognition (detecting and quan-

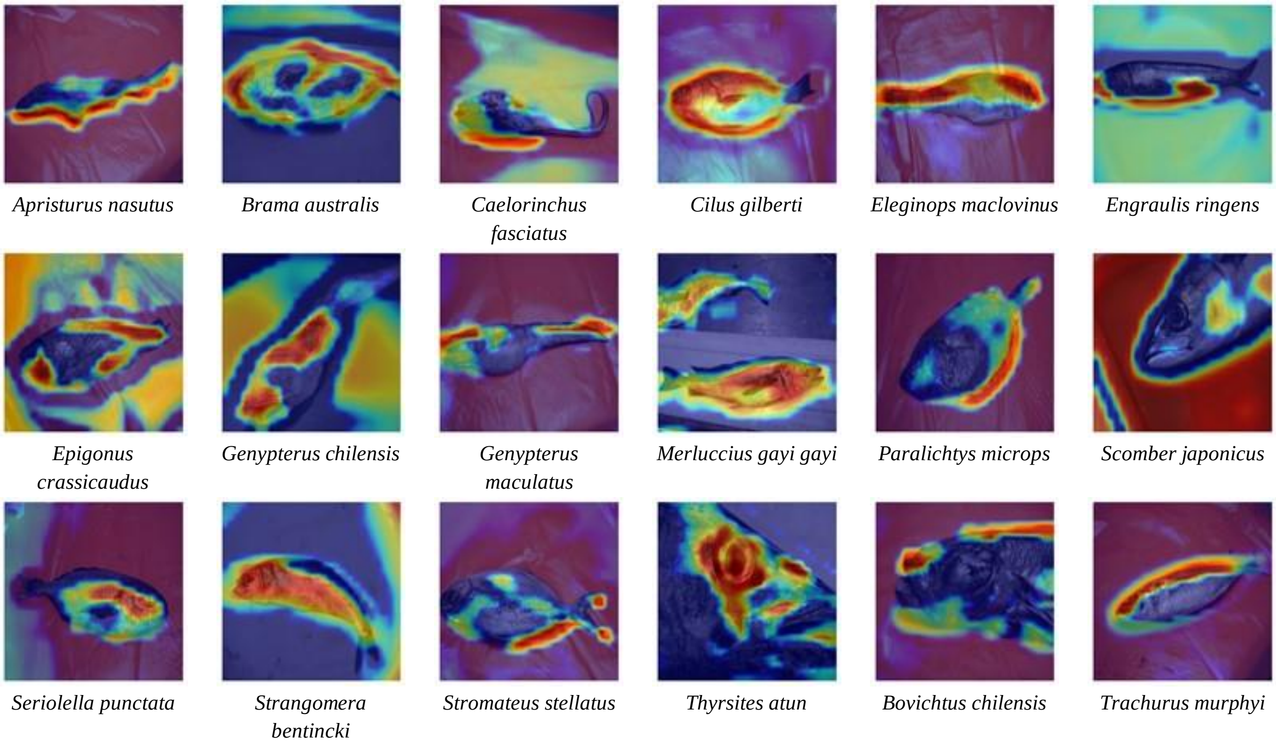

Figure 7. Grad-CAM visualization of randomly selected images from each species included in the study.

tifying individuals), measurement (assessing individual characteristics like weight, size, sex, etc.), tracking (where feasible), and classification (identifying species and pertinent features). Traditional reliance on visual methods, whether direct or via images/videos, encounters challenges including high costs, low throughput, subjectivity, and observer biases, compromising data reliability (Benoît et al. 2009, Cahalan et al. 2016, Snyder & Erbaugh 2020). Additionally, imaging devices facilitate data collection in hazardous environments, mitigating risks to human operators. Furthermore, addressing the knowledge and management gaps related to bycatch necessitates a multi-faceted approach, starting with precisely identifying the fisheries and species affected by bycatch (Soykan et al. 2008, Poisson et al. 2022). This imperative paves the way for the development of targeted technological solutions and research, particularly in species identification, such as the case of this work. For example, the *iObserver* device (Vilas et al. 2020), specifically designed for fishing vessels, automatically captures and processes catch images for species identification and quantification. This system exemplifies the integration of image processing and real-time data analysis, leveraging open-source image recognition software for accurate species detection and quantification, becoming essential in evolving visual tracking systems that autonomously detect, classify, and enumerate various fish species based on video footage from fishing operations. Such integration and recent advancements in computer vision systems highlight the growing feasibility of enhancing electronic monitoring in fisheries, providing comprehensive records of catch and bycatch that outstrip the capabilities of manual observers (Khokker et al. 2022, Lekunberri et al. 2022, da Silva et al. 2023).

Noteworthy is the realization that fishing vessel conditions are seldom ideal, with each fishery having distinct operational procedures and fishing gears of varied selectivities. Challenges like variable lighting, weather conditions, and the need for extensive, annotated datasets necessitate tailored solutions to improve system accuracy and reliability. Thus, accurate identification of individual fish species becomes paramount in environments where multiple species coexist and traditional counting methods often fall short, yielding unreliable or inconsistent data. The CNN-based species classification developed in this study is of particular importance as it provides the necessary building blocks for implementing integrated systems that further aid in monitoring fisheries, highlighting the significance of our research in contributing to the broader objectives of sustainable fisheries management and ecosystem conservation. In this context, effective species classification emerges as a critical component for comprehensive surveys and monitoring of fisheries activities. Such classification aids in detecting non-targeted species, facilitates the implementation of effective control measures, and contributes to the reduction of bycatch (Siddiqui et al. 2018, Hridayami et al. 2019, Agarwal et al. 2021). Consequently, integrating these considerations with the advancements in computer vision and electronic monitoring emphasizes the potential for significantly enhancing fisheries management's accuracy, efficiency, and sustainability. Combining rigorous species identification with innovative monitoring technologies, this dual approach addresses the complexities and challenges inherent in modern fisheries management, especially in diverse and dynamic marine ecosystems.

CNN-based models offer state-of-the-art classification accuracy, even when working with limited datasets. However, the manual collection and curation of large image repositories remain significant constraints, underscoring the need for techniques that utilize artificially generated training data. Data augmentation -employing techniques such as flips, rotations, shifts, shearing, and zooming- continues to be one of the most accessible and effective strategies for increasing dataset diversity and improving generalization (Mumuni & Mumuni 2022, Kumar et al. 2024, Wang et al. 2024). These conventional methods can substantially enhance the robustness of models across varied scenarios, particularly in fisheries research, where obtaining comprehensive imagery of underrepresented species can be challenging (Ben-Tamou et al. 2022).

Nevertheless, traditional augmentation approaches have inherent limitations, as they do not fully capture the complexity of real-world conditions or adequately address extreme data imbalances. More advanced techniques, such as generative adversarial networks or class-specific synthetic image generation, could yield higher-quality augmented samples and improve model performance (Mumuni & Mumuni 2022, Kuntalp & Düzyel 2024). However, implementing these sophisticated methods requires specialized, domain-specific procedures. Given that the current study represents an initial effort in this field, extending the scope to include such advanced methods was not feasible. Future research will focus on integrating these more specialized augmentation strategies, particularly for underrepresented and visually complex species.

As stated in the Introduction section, the Chilean fisheries administration established the Fisheries Observer and Monitoring Program (FOMP), which incorporates various tasks aimed at achieving the objectives outlined in the new fisheries regulations, redirecting its focus towards the research and monitoring of discard and bycatch in pelagic purse-seine and demersal trawling fisheries. In this context, the FOMP provides information for developing national plans by fishery/fleet to help reduce discards of target and non-target species and reduce bycatch of birds, mammals, and marine reptiles (turtles). The FOMP, with its focus on the conservation and management of hydrobiological resources through data collection, could directly benefit from this research by implementing the proposed models in their sampling and data collection processes, thereby helping to identify different species better and build datasets for the recursive improvement of the implemented models.

In wildlife sciences, emerging methods for data collection are constantly being developed (e.g. unoccupied aircraft systems, camera tags, and satellite imagery). In the fisheries science framework, the latter poses challenges in overcoming the constantly generated flood of information and properly analyzing the data to generate knowledge. To address this issue, there is a growing investment in using artificial intelligence (AI) for automated image data processing. Angliss et al. (2020) outline five key stages of implementing an AI project: scoping, data preparation and annotation, model selection, training, testing, model evaluation and re-training, deployment, and integration. In that sense, future work aims to build upon the good results of this article, integrating them into a broader framework that leverages computer vision to recognize onboard fish, quantify catches, and detect suspicious activities such as discards and bycatch. This comprehensive approach can greatly benefit Fisheries Observer programs, by integrating this automated species classification model into a broader framework that uses computer vision and segmentation techniques for the identification of multiple fish species, automatic measurement of lengths and weights, among other direct applications, thus enhancing compliance and contributing to the sustainable management of Chilean fisheries and broader ecosystems.

Through an examination of the dynamic and transdisciplinary facets of the issue, deep learning methods could be further integrated into more intricate management models, employing automated fish recognition through computer vision systems. Thus, this approach must recognize the interconnectedness of ecological and human dimensions in the context of bycatch, deviating from conventional methodologies and extending beyond immediate benefits for fisheries management. Its potential in accurate bycatch estimation establishes a cornerstone for sustainable practices. This investment in advanced technologies addresses the current complexities of global bycatch. It lays the groundwork for future mitigation efforts, highlighting the transformative power of integrating deep learning and computer vision in marine conservation and fisheries management.

Credit author contribution

E. Alvarado: conceptualization, investigation, methodology, software, formal analysis, validation, writing - original draft; F. Plaza-Vega: conceptualization, investigation, software, formal analysis, visualization, validation, writing - original draft; C. Montenegro: data curation, supervision, writing - review & editing; O. Saavedra: supervision, writing - review & editing. All authors have read and accepted the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

Data availability

The code and data used in this study are available on GitHub (https://github.com/ealvnrz/DL_fish_classification).

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