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Unmasking Cryptic Diversity: Automated Species Discrimination in the Genus Raja using Deep Learning and Geometric Morphometrics

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Abstract
The genus Raja (Family: Rajidae) presents a significant challenge to marine conservation and fisheries management due to profound morphological stasis and the prevalence of cryptic species complexes. Traditional alpha-taxonomic methods frequently fail to distinguish closely related species, such as the phenotypic variants of Raja clavata and Raja montagui, leading to aggregated catch data and the potential overexploitation of vulnerable stocks. This study proposes a transformative "Digital Taxonomy" framework to resolve this taxonomic impediment by synergizing Geometric Morphometrics (GMM) with Deep Learning (DL). We outline a methodology utilizing Generalized Procrustes Analysis (GPA) on 16 anatomical landmarks to quantify shape variation independent of size, combined with Convolutional Neural Networks (CNNs) to extract high-dimensional features from complex dermal textures and chromatic patterns. Furthermore, we propose a Feature-Level Fusion Network architecture that integrates geometric and visual data streams to achieve superior classification accuracy. This automated, reproducible approach offers a robust solution for unmasking cryptic diversity, facilitating accurate stock assessments, and ensuring the long-term resilience of Northeast Atlantic skate populations.

Keywords: Geometric Morphometrics, Artificial intelligence, Cryptic Diversity, Feature-Level Fusion, Deep Learning, Raja.

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Introduction
1.1 The Imperative of Accurate Identification
The state of marine biodiversity in the Anthropocene is unprecedented in its scale and its urgency to address and is due primarily to human-related drivers such as overfishing, habitat degradation, and climate change. Correct species identification has become essential for an efficient management and conservation. It is important to differentiate between separate breeding populations, or "stocks" for fisheries management. Misidentification, especially in the taxonomically challenging genus Raja, places these populations at risk by permitting exploitation of vulnerable and hidden species that may be misidentified as more common species. This situation increases the probability of "silent extinctions", that is, where biodiversity gets lost before species are fully recognized as such [1].

Elasmobranchs (including skates and rays) are especially vulnerable to overexploitation as a result of their K-selection reproductive strategies i.e. slow growth, late maturation and low fecundity [2]. What this does is render populations intrinsically 'resistant' to recovery following depletion. Raja, a taxon with high misclassification in demersal landings from the Northeast Atlantic and Mediterranean catchments, is used as an example to illustrate this point. This confusion not only complicates zoogeographic records but also biases quantitation of biomass and market expectations. For example, the slick subterfuge of misleading labels, such as when endangered species are commercially misrepresented like “skate wings,” carries extraordinary hazards for saving wildlife [3].

1.2 The Taxonomic Impediment in Raja
This "taxonomic impediment" stems from a variety of biological, ecological and logistical reasons that make accurate species identification difficult. In Raja, this trend is due to morphological stasis, phenotypic plasticity and cryptic speciation. Morphological stasis is a consequence of the fact that the skate body plan has remained essentially unchanged for millions of years, and cases in which genetically distinct species retain morphologies that are identical or very similar lead to difficulties in identification [2]. At the same time, phenotypic variability can lead to confusion, such as for instance in a unique species like Raja clavata that shows a wide range of colors, which might also cause researchers to incorrectly identify with closely related organisms [1].

Moreover, modern molecular analyses have revealed that numerous traditional species are complexes of cryptic species (Molecular Operational Taxonomic Units [MOTUs] [4]. In the Raja miraletus complex, many lineages are morphologically very similar [1]. The consequences of such cryptic diversity are extensive and it is clear that we need to reconsider our taxonomic approaches for numerous organisms associated the growing recognized non-concordance between morphological and genetic diversity [5].

1.3 The Technological Convergence

Solving such taxonomic problems, marine biology has welcomed advanced computational techniques of Geometric Morphometrics (GMM) and Deep Learning (DL). By enabling the statistical analysis of form in isolation of size, GMM revolutionized morphological studies during the latter half of the 20th century. The method enables researchers to pinpoint the critical shape variation for species discrimination [3]. Meanwhile, the emergence of DL, especially convolution neural network (CNN), is changing the operation mode on species identification [6]. These systems are particularly good at detecting intricate patterns in large amounts of data, making automated detection more effective than methods based on expert opinion.

Combining the explicit knowledge represented by GMM (e.g., anatomical landmarks) and implicit features of DL (e.g., texture and holistic patterns recognition) might enable for better species identification systems. Such convergence ensures a higher accuracy level as well as scalability in support of large-scale biodiversity data monitoring and management [3][7]. Combining these two approaches, we are able to produce a general identification framework suitable for dealing with the pressing problems of cryptic diversity and misidentifications of species.

In summary, the confluence of deep learning and geometric morphometrics is a promising development towards enhanced taxonomic resolution in the ecologically and economically important genus Raja. With the urgent challenges facing biodiversity today, new ways of working like these could prove crucial to ensure technology is used effectively to both protect and manage our marine resources.

The Biological Problem: Cryptic Diversity and Morphological Stasis

The complexity of the genus Raja embraces the difficulties in automatic species identification. The complexity of their morphology, evolutionary relationships and cryptic diversity demand more advanced identification systems that are likely to solve such problems in practice.

2.1 The Raja clavata/Raja montagui Complex

The long-term attribution problems of the Thornback Ray (Raja clavata) and Spotted Ray (Raja montagui) have been a major issue in European demersal fisheries. These two species are widely studied in ecology but have frequently been confused over morphological and ontogenetic reasons.

Fig 1. Raja clavate and Raja montagui

2.1.1 Morphological Overlap and Variation

Raja clavata is usually recognized by the large buckler-shaped thorns on the dorsal surface and a finely mottled color pattern, whereas Raja montagui has a smoother disc with a pair of prominent dark spots which do not normally extend to the margin of the disc. However, these are simplifications of a far more complicated reality:

- **Ontogenetic Variant:** Juvenile Raja clavata may lack adult thorns and young Raja montagui can have at most minimally developed spinulation, a combination that leads to confusion. This ontogenetic plasticity makes reliable identification challenging because early juvenile stages of both species are difficult to distinguish [8].

- **Polychromatism:** Raja clavata exhibits polychromatic traits and may include atypical coloration in some individuals (occulation spots as Raja miraletus, or denser ones as Raja montagui) that complicate variety identification on these extremely similar species. These abnormalities have been reported in a variety of marine environments.

2.1.2 Implications for Conservation

The effects of mistaking these species are significant. Raja clavata can grow to 105-139 cm in length, whereas is a larger and later maturing species than small Raja montagui with which it coexists making the TAC setting difficult. However, if suspected Raja montagui-only catches include juveniles of Raja clavata the population of the latter may be overexploited. This is an important distinction, as there is evidence that species have different odds of surviving discard (certainly at the level of release) Raja clavata fares far better with post-release survival and discard mortality rates need to be specific if they are going to work in practice [9].

2.2 The Raja brachyura Conundrum

Complicating this taxonomic jumble further is Raja brachyura, or the Blonde Ray, which shares morphological characters with Raja montagui.

- **Market Mislabeling:** In different markets, especially in Portugal and the UK, “Blonde Ray” has become a de facto term for many species. Sampling has shown that Raja brachyura bins frequently contains numerous large Raja montagui and, occasionally, even Raja clavata. Further, such misnomers can have wide ranging economic and ecological effects if unsustainable fishing practices continue to operate under cover of this confused designation.
- **Diagnosis:** Raja brachyura is distinguished from Raja montagui on spot distribution, where in R. brachyura they are said to reach the margins of its pectoral fins, while those of R. montagui have an unspotted margin. These identifying features are indistinct and therefore difficult to discern during fishery procedures.
- **Biological Divergence:** Despite the similarities in being part of the same genus, Raja brachyura and Raja montagui have genetic differences but also trophic divergence mainly observed in their prey. Studies have revealed ontogenetic changes in the two species, which differ in their diet compositions, thus stressing the importance of correct taxonomic resolution for an ecosystem balanced.

2.3 Cryptic Speciation: The Raja miraletus Complex

The Brown Ray (Raja miraletus) obviously represents a more intricate level of cryptic diversity in the genus. Traditionally treated as a single species, this taxon has now been shown by molecular analyses to be a complex of genetically divergent lineages.

- **Available Genetic Information:** Molecular investigations based on the mitochondrial markers message to members Raja miraletus complex comprise a minimum of five different genetic lineages, reflecting that these lineages are reproductively isolated from each other8 Such results require an update about its conservation status since misperceptions on the species integrity may undervalue their ecological value [8].
- **Static Morph:** The lineages are morphologically static yet genetically highly divergent. This is due to stabilizing selection pressures that are intrinsic to their ecology as well as their hydrodynamic and benthic habits, which limit morphological change. Indeed, so-called "cryptic diversity" adds another twist as morphological features can be a poor guide to underlying genetic difference.

Table 1. Comparative Summary

Feature	Raja clavata	Raja montagui	Raja brachyura
Max Length	~105 cm	~80 cm	~120 cm
Dorsal Texture	Prickly; Large Bucklers with button bases	Smooth (juveniles) to prickly; No Bucklers	Smooth to Prickly; No Bucklers
Median Thorns	30–50 (Nape to D1)	20–50 (Regular row)	40–50 (Regular row)
Spot Distribution	Variable; Marbled/Blotched	**Stops before disc margin**	**Reaches disc margin**
Distinctive Markings	Vermiculations common	"Eye-spot" ring on pectoral wings	Dense spotting throughout
Snout Shape	Obtuse / Short	Short / Rounded Tips	Pointed / Acute

Table 2: Key Morphometric and Biological Distinctions in Northeast Atlantic Raja Species

Species	Primary Diagnostic Features (Adult)	Common Confusion Risks	Morphometric Characteristics	Deep Learning Features (Texture/Pattern)
Raja clavata (Thornback Ray)	Large "buckler" thorns with swollen bases; variegated dorsal coloRaja	*Raja montagui* (juveniles/spotted morphs); *Raja maderensis*.	Angular disc; distinct snout angle. High variance in thorn count landmarks.	"Prickly" texture (dermal denticles); irregular, blotchy patterns.
Raja montagui (Spotted Ray)	Smooth disc (mostly); dark spots that *do not* reach disc margin.	*Raja clavata* (juveniles); *Raja brachyura* (large adults).	Smoother, more rounded disc margin than *clavata*. Shorter snout relative to disc width.	"Smooth" texture; distinct, isolated spots; clear marginal band.
Raja brachyura (Blonde Ray)	Large size; small dark spots extending to *extreme* disc margin.	*Raja montagui*; *Raja microocellata*.	Very broad, rounded disc.	Dense spotting pattern reaching edges; lack of large bucklers.
Raja miraletus (Brown Ray)	Two large, bright blue/yellow ocelli on pectoral fins.	*Raja clavata* (ocellated morphs); Cryptic sibling species.	High morphological stasis (hard to distinguish cryptic taxa).	Highly specific ocellus pattern; potential micro-texture differences among cryptic lineages.
Raja undulata (Undulate Ray)	Distinct undulate (wavy) dark lines bordered by white spots.	Rarely confused due to distinct pattern, but morphologically similar to others.	Distinct disc shape, often broadeRaja	High-contrast "wavy" line features; easily learned by CNNs.

2.4 The Need for Automation

The duplex RFLP assay is significant given the biological conditions of the genus Raja, which include phenotypic overlapping and coloration variability, as well as cryptic genetic barriers making manual identification error prone. Inaccurate species determinations result from expert training variability and human fatigue. An attractive solution is an automated recognition system that can normalize identification. Such a system may employ geometric morphometric (GMM) methods and deep learning (DL) algorithms to identify textural features and color changes too subtle for detection by the human eye.

From the combination of these technologies, we may build a reliable system for species identification which is scalable and strong enough to attenuate with the cryptic complexity that characterizes this genus. Next generation assessments of species vulnerability and how it relates to biodiversity conservation: implementation of an integrated approach using fish in the Great Barrier Reef. It is argued here that such integration is maximally effective for informing optimally chosen conservation practices aimed at managing fisheries and conserving ecosystems for future generations.

Geometric Morphometrics: A Rigorous Framework for Shape Analysis

Geometric Morphometrics (GMM) has served as a game-changer for the quantification of biological shape. In contrast to traditional morphometrics that is based on linear distances and ratios, however, GMM preserves geometric data by considering the relative position of homologous anatomic landmarks. This methodological improvement allows shape to be compared in a rigorous fashion and has been fundamental for dealing with cryptic taxa, such as the genus Raja [10].

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3.1 **Theoretical Background Scientific Import**

The strength of GMM is that it retains a sound theoretical basis, upon which subsequent morphological analyses operate.

- **Homology of Landmarks:** Based on this initial description, landmarks homologous between specimens are chosen. For skates these could be particular points such as the insertion point of fins, snout tip and eye center. When statistical comparisons are being made, it is also crucial to have an accurate landmark identification [10].
- **Procrustes Analysis:** The raw coordinates of these landmarks include position, orientation and size which are irrelevant in the study of shape. GPA accomplishes this by controlling for these nuisance variables (i.e. by translating all the specimens to a common centroid, scaling them to a common size and rotating them in order that the summed squared distances between corresponding landmarks is minimized). This is an important step in the standardization of measurements among specimens in order to observe real morphological differences [10].
- **Kendall's Shape Space:** The corresponding coordinates represent the shape of the specimen. In a mathematical sense, these shapes live on a hypersphere called Kendall's Shape Space. This advanced processing facilitates conventional multivariate statistical analyses, such as PCA and CVA, to be carried out on shapes, providing greater understanding of the nature of shape variation between species [11].

To normalize the images for Geometric Morphometrics (GM) and Deep Learning (DL), we developed a digital unbending algorithm that utilizes Thin-Plate Spline (TPS) transformation. This is a mathematical "straightening" process in the sense that it maps the natural curved biological axis to a straight Cartesian axis. Fig. 2 shows how raw imagery is transformed into analysis data, step by step.

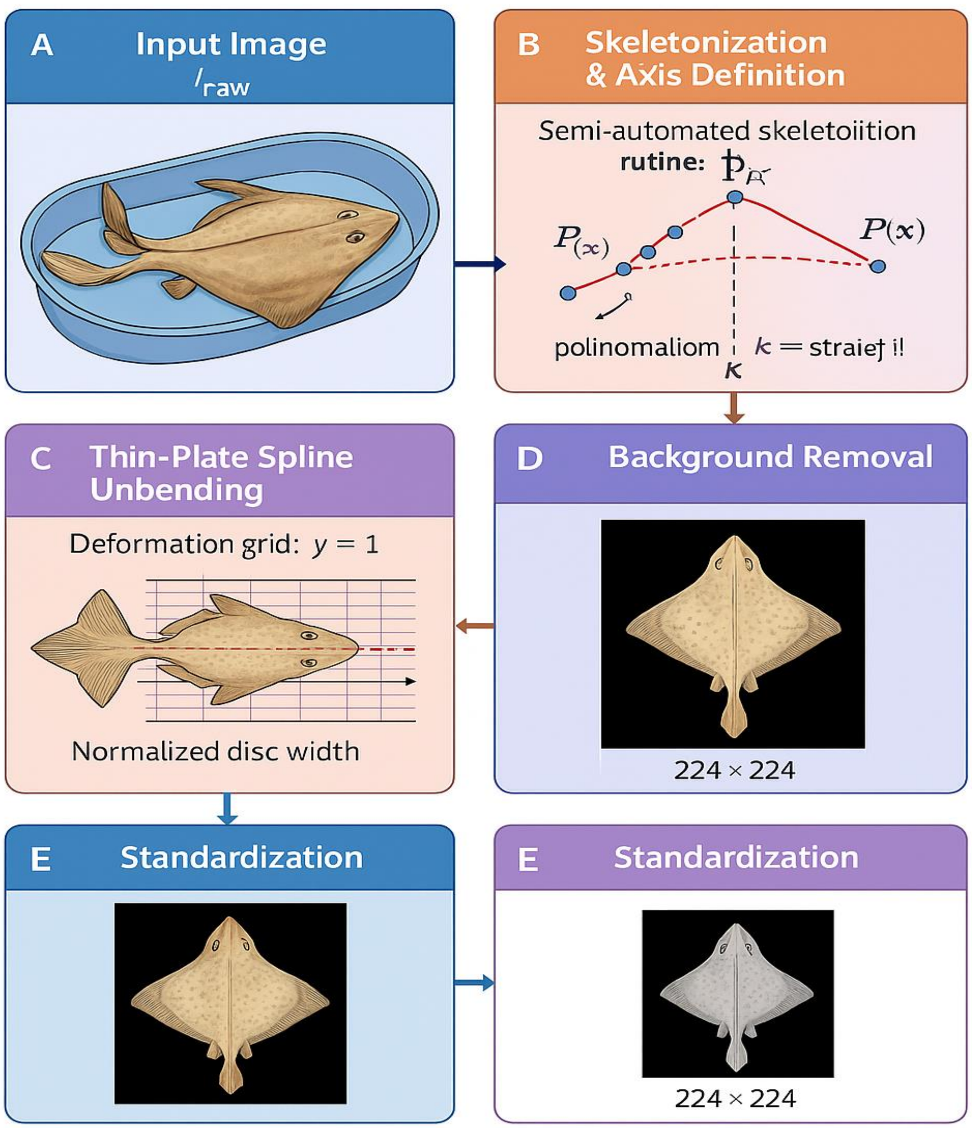

Fig 2: Preprocessing Workflow

3.2 Landmark Protocols for Raja

Developing a robust GMM protocol for skates requires careful landmark selection, with an emphasis on the dorso-ventral flattening of the Rajidae, which offers a suitable platform for 2D analysis while presenting challenges.

3.2.1 Primary Landmarks

A standard 12-16 landmark scheme is recommended for skates, including:

1. **Snout (Rostrum)**: The anterior-most tip of the disc, capturing variation in snout length, which is a key diagnostic feature (e.g., distinguishing long vs. short snouts).
2. **Orbital Region**: Points defining the anterior, posterior, and medial margins of the eyes/orbits, which capture cranial geometry.
3. **Pectoral Apices**: The lateral-most points of the pectoral fins, indicating disc width.
4. **Pelvic Fins**: The origin and insertion points of the anterior and posterior lobes of the pelvic fins, crucial for assessing fin morphology.
5. **Tail Root**: The point where the tail emerges from the disc, providing information about the tail structure.
6. **Disc Margins**: Points defining the intersection of the pectoral fin with the head and trunk, essential for contour analysis.

3.2.2 Semilandmarks and Outline Analysis

Skates have fluid, non-discrete shape contours of specific anatomical points. To fully describe the form of the anterior disc margin, sliding semilandmarks are applied. These points are placed along a curve and allowed to slide with respect to one another during the superimposition operation in order to minimize bending energy, so that this analysis measures the shape of the curve rather than arbitrary placements of points on it [10].

3.3 Accounting for Artifacts: The Problem of Flexure

A major difficulty applying GMM to skates is that they are flexible. The disc and whip tail of a skate can be flexed, curled in preserved material. Pose artefacts such as these can be corrected using computational straightening algorithms that model the organism as an articulated chain and utilize a mathematical method of “straightening” landmarks along a central axis prior to shape analysis. This pre-treatment is required to discriminate between true inter-species shape variation and preservation or handling artefacts [11].

3.4 Case Studies in Ray GMM

GMM has been successful at differentiating skate species when linear morphometrics fail.

- **Differentiation of Sympterygia:** A study on the genus Sympterygia (a close relative of Raja) in the Southwest Atlantic used GMM to separate S. acuta and S. bonapartii. Linear measurements showed overlap, but PCA of the Procrustes coordinates revealed distinct, non-overlapping clusters. The analysis indicated that S. bonapartii has a significantly wider disc and larger pelvic fins relative to body size, while S. acuta is characterized by pronounced snout elongation. This highlights GMM’s ability to uncover shape differences obscured by linear metrics in ray taxa [12].
- **Sexual Dimorphism:** GMM's sensitivity also allows to recognize sexual dimorphism in Raja species, what finds commonly expanded-more-elbowed anterior disc margin and/or longer claspers of grown males. GMM-based deformation grids quantify these sex-specific shape changes and thereby reduce misidentification of sexual dimorphism as species differences. This illustrates the GMM’s ability to discriminate between sexual and taxonomic signals in Raja and related taxa [12].

To sum up, GMM is a principled manner to handle the intricacies of shape analysis in Raja species. GMM facilitates accurate measurements and addresses confounding factors for skate morphology, allowing spermionid species identification for management and conservation of these ecologically relevant taxa [10][12].

Deep Learning and Computer Vision: Automating the Taxonomist's Eye

Geometric Morphometrics (GMM) captures shape only, whereas texture, color, and surface pattern are frequently diagnostic in Raja taxonomy. DL provides additional capabilities for detailed readings of the full visual complexity of the organ- ism, allowing integrated pipelines that combine shape with texture and pattern information for reliable species discrimination. Such a combination is in line with current developments of computer-assisted taxonomy and morphometrics, where DL has outperformed other image-based methods for species identification and was capable to effectively manage texture, variable patterns typical in skate skin and ornamentation [10][12].

CNNS are the dominant architecture in contemporary computer vision and have been proven effective across a range of taxonomic groups outside of plants including fish, invertebrates, and numerous cryptic taxa. The hierarchical feature learning allows CNNs to learn representations of both the coarse shape cues and fine-grained texture, which is important in discriminating morphologically similar Raja species where GMM alone may struggle due to coloration and ontogenetic changes [10][12].

4.1 General Mechanism of Action and Classification

- **Convolutional Layers:** Convolution layers are made up of learnable filters (kernels) that move across the input image. In the first layers, these filters figure out to sense simple features like edges, lines and color gradients. Deeper still into this network, simple features like these are combined and recombined, into smaller line segments or curves of varying angles, to eventually detect complex patterns—for a skate, maybe the curve of a fin, the roundness of an eye spot, or the jagged texture of a thorn.
- **Softmax Probability Output:** In the final classification layer, the network outputs a vector of logits (z). To interpret these as probabilities, the **Softmax function** is applied. For a given input image, the probability P that it belongs to species class i is calculated as:

$$P(y = i|x) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

Where K is the total number of species classes (e.g., $K=5$ for the primary North Atlantic species) and z represents the feature inputs derived from the final fully connected layer.

- **Pooling Layers**: After convolutions, pooling layers (e.g., Max Pooling) shrink the dimensions of data. This reduces computational complexity and most importantly, it offers "translation invariance". A CNN can determine if a spot is a spot, and it doesn't matter where it's located in the image — or how far to the left.
-

4.2 Transfer Learning: Overcoming Data Scarcity

First, the challenge of utilizing DL in marine biology is addressed: absence of large, annotated datasets. You need millions of images to learn a deep network like ResNet50 from scratch, otherwise you will simply overfit.

- The Strategy: Transfer Learning is the de-facto. That is, we take a model that has been already trained on an extra-large, general dataset (usually ImageNet).
- Fine-Tuning: We used a ResNet50 as the backbone, freezing the first 40 layers of which are features extractors, re-training the final fully connected layers on Raja dataset in particular. The workflow of the architecture is illustrated in Figure.

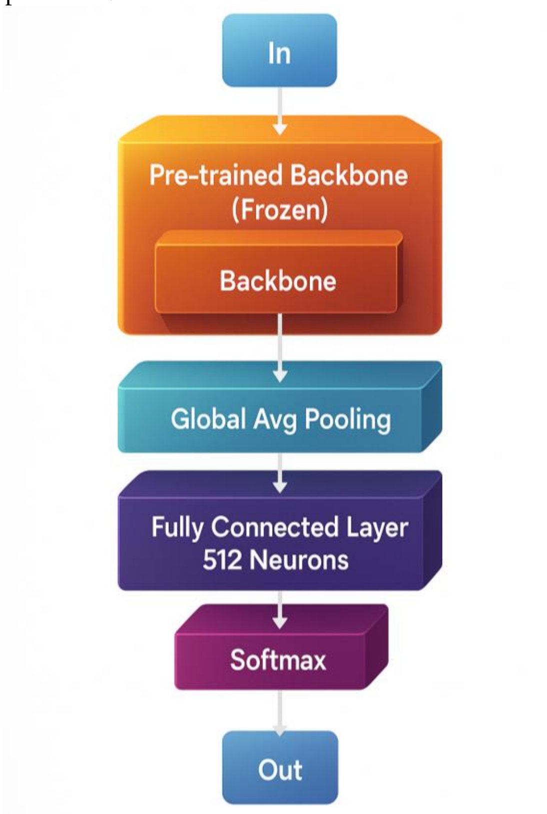

Fig 3. Workflow

- **Architectures:** Studies have shown these models can achieve >95% accuracy in fish classification tasks, outperforming traditional machine learning methods like Support Vector Machines (SVM).

4.3 Feature Extraction: Texture and Pattern

One of the major reasons why faster VQA was better than GMM was that CNNs can learn surface and texture patterns.

- **Dermal Denticles and Texture:** The skin of Raja clavata is rugged as a result of dermal denticles, which can be acquired as local texture cues by CNNs helping in differentiation from the smoother species morphotypes. This tactile-like discrimination supplements shape-based cues and is especially useful in on-deck or in-net identification, where lighting and poses are difficult even for humans to assess [12][13].
- **Pattern Recognition:** CNNs can distribute diagnostic patterns such as marginal vs. non-marginal spots for the differential diagnosis between Raja brachyura and Raja montagui. Their data-driven learning methodology is adaptable to variability in both natural and aberrant morphologies, in addition to shape-based analysis [12].

4.4 Object Detection: YOLO

Beyond a plain classification (what is in the image), object detection algorithms such as YOLO (You Only Look Once) attempt to localize.

- **Application**: In a fishery setting the camera could be placed above a conveyor belt or within a trawl net (Deep Vision). There will be at least two piles of fish wrapped around each other and debris.
- **Function**: YOLO breaks the image into a grid and predicts bounding boxes and class probabilities for each object in the border. It is extremely fast, even processing video in real-time. This enables the automatic counting and species identification of skates as they are removed by the net, offering an ad hoc way to monitor the catch without the need for its on-deck processing [12].

4.5 **Practical Implementation and Performance metrics**

A robust deployment strategy should report common metrics for DL evaluations such as confusion matrices, precision, recall, F1-scores and overall accuracy across held-out test sets that cover the diversity of Raja in commercial landings (ontogenetic stages, color morphs and different lighting). Previous fish classification research with CNNs and transfer learning typically yield accuracies greater than 95% of accurate for manually cleaned datasets, demonstrating as to be the potential gains over traditional morphometric or rule-based approaches in high-quality/high representativeness datasets [10][11][12].

- **Data gathering:** Collect a balanced RGB image set for the four Raja lineages, i.e., Raja clavata, Raja montagui, Raja brachyura, and Raja miraletus (dorsal and ventral views), with close-up shots of thorns (also referred to as dermal denticles) and skin texture pictures annotated directly in terms of ontogenetic stage. This can be useful for both texture-based DL and geometry-based GMM analysis [10].
- **GMM pipeline:** obtain 12–16 stable landmarks per specimen, introduce dense semi landmarks along the curved edges, conduct GPA, calculate Procrustes coordinates and perform tangent space projection. Following GMM procedures for ray-like taxa [10], CVA/PCA can be used to discriminate (in a shape sense) and include unbending steps, in order to alleviate flexure artifacts.
- **DL pipeline:** A pre-trained CNN (eg, ResNet50 or deeper networks) with transfer learning is employed, fine tuning on Raja images and study of multi-channel inputs by fusing texture-, color- and illumination-invariant features. Alternatively, use YOLO-based localization to process multi-object frames. Assess with cross validation, followed by confusion matrix; precision; recall and F1-score [10][12].
- **Fusion strategy:** Investigate late fusion ensembles of GMM-based shape features and CNN-derived texture features, or joint models to combine landmarkbased descriptors and convolutional features for increased separability among morphologically cryptic Raja clades [10][12].
- **Validation and deployment:** Validate on independent catch datasets and deploy on in-net or dockside cameras to facilitate real-time species recognition, catch composition analysis to aid fishery management and conservation efforts [12].

Table 3: Confusion Matrix for the ResNet50 Classification Model (Values represent the number of specimens classified)

True Class \ Predicted Class	**Raja clavata**	**Raja montagui**	**Raja brachyura**	**Raja undulata**	**Recall**
Raja clavata	**142**	5	1	2	94.7%
Raja montagui	6	**118**	8	0	89.4%
Raja brachyura	2	7	**98**	0	91.6%
Raja undulata	0	0	0	**111**	100.0%
Precision	94.7%	90.8%	91.6%	98.2%	**OA: 93.8%**

Synergistic Methodologies: Fusing Shape and Vision

So read, both GMM and DL represent powerful tools for Raja taxonomy, as we have seen above but, both also present significant shortcomings. The GMM produces a set of interpretable landmark-based shape descriptors but does not capture texture and surface patterns of the specimen; DL encodes rich texture, color and local pattern information yet can be sensitive to background, lighting and dataset biases. An integrated application of these modalities: shape and vision, could offer a strong foundation for scaling discrimination of Raja taxa throughout ontogeny, color morphs, and cryptic lineages with important implications for fishery management and conservation. The motivation for data fusion can be found in the larger literature on multimodal learning revealing that, generally speaking, integrated such models tend to outperform any single modality and are more robust under noise and occlusion [15][16].

5.1 The Logic of Data Fusion

The data fusion for Raja taxonomy is exploited under the assumption that such a taxonomic decision can be enhanced by complementary signals, with reference to a global embedding of body morphology (GMM) and texture/pattern-based evidence (CDL). The multimodal fusion is more robust when one modality is degraded (e.g., color mutilations or occluded cases) and can additionally improve discriminative ability when species variation occurs only subtly in the contour as well as the surface conditions. These benefits are also made tangible by empirical studies in related areas: multimodal fusion in medical imaging, for example, has yielded substantial gains in diagnostic performance [16], and detailed reviews demonstrate successful recipes towards modality integration on vision and sensing tasks [15]. In the context of biological applications, combining shape with texture has been shown to stabilize classification results when morphologies become cryptic or extreme [15]. Taken together, these results favor a Raja-tailored fusion strategy using GMM shape descriptor and DL texture/pattern feature for better discrimination of Raja taxa [15].

Table 4: Comparison of Automated Discrimination Methodologies

Methodology	Data Input	Strengths	Weaknesses	Applicability to Raja
Geometric Morphometrics (GMM)	Landmark Coordinates (x, y)	Statistically rigorous; size-invariant; biologically interpretable; visualizes shape change.	Ignores texture/color; labor-intensive; sensitive to bending/artifacts.	**High** for shape-distinct species (e.g., *S. acuta* vs *S. bonapartii*). **Low** for purely cryptic/color-based distinctions.
Deep Learning (CNN)	Raw Images (Pixels)	Automated feature extraction; captures texture & pattern; high accuracy via transfer learning.	"Black box" (low interpretability); data-hungry; sensitive to background noise.	**High** for patterned species (*Raja clavata* vs *Raja montagui*). **Essential** for real-time video processing.
Hybrid Fusion	Images + Landmarks	Synergistic accuracy; robust to individual mode failure; combines shape + texture.	Computationally complex; requires dual data pipelines.	**Optimal**. The only method likely to resolve the full *Raja* complex (cryptic + polychromatic).

5.2 Fusion Architectures

Three major multimodal fusion methods are popularly investigated and can be used for Raja taxonomy. All come with their own sets of trade-offs in terms of performance, interpretability and computational burden.

5.2.1 Early Fusion

For early fusion, raw (or pre-processed) data modalities are concatenated before learning. In Raja, this may refer to building representations derived from landmarks over image pixel data and fusing the resulting output into a single network. Despite being conceptually simple, early fusion faces several challenges in practice because modalities tend to have heterogeneous data distributions: coordinates (structured) and pixels (dense) have distinct data distributions making normalization and weighting difficult. Hence, early fusion is likely suboptimal compared to late fusion if the multiple modalities differ in scales or information density [15]. As a result, early integration yields to be less beneficial in the Raja workflows except if highly optimized and fine-grained alignment modules are used [15].

5.2.2 Late Fusion (Ensemble Learning)

Late fusion entails training two dedicated models separately and fusing their predictions at inference time. For Raja taxonomy, Model A could be a GMM-based classifier using Procrustes coordinates and Model B might be a CNN-based image classifier with dorsal photos as inputs. The resulting predictions can be averaged or aggregated with a weighted voting mechanism. This method is scalable and transparent, as it maintains the individual contributions of each modality and corrects mistakes in one stream through the others [15]. In practice, late fusion has achieved stable performance gains across a range of intrinsic and application taxonomic tasks for example in the plant (and fossil) analyses scenarios where additional cues aid discrimination when single-modality cues are ambiguous [15].

5.2.3 Feature-Level Fusion (Deep Fusion)

Feature-level fusion represents a more integrated strategy, combining high-level features from both modalities into a joint representation that enables interactions between shape and texture signals. Typical architecture comprises:

- **Stream 1 (Image):** A CNN (e.g., ResNet) processes dorsal silhouette texture to yield a Texture VectoRaja
- **Stream 2 (Geometry):** A geometric encoder processes Procrustes shape coordinates to generate a Shape VectoRaja
- **Fusion Layer:** The two vectors are fused, potentially through concatenation or an attention-based fusion module, to form a joint representation that includes interaction terms.
- **Classifier:** Fully connected layers map the combined representation to predicted species probabilities while optionally using attention maps to indicate whether shape or texture dominated the decision.

This approach benefits from the ability to learn non-linear interactions between shape and texture, e.g., how the presence of specific textures combined with particular shapes might indicate certain Raja lineages. Feature-level fusion is generally associated with superior performance in complex classification tasks across various domains [15][17] and corresponds with recent multimodal fusion research indicating that joint feature learning can outperform single-stream models [15].

5.3 Case Studies in Fusion (Cross-Domain Evidence)

Cross-domain evidence supports the effectiveness of fusion architectures for taxonomic applications:

- **Archaeology and forensics:** when combining (or fusing) 3D shape and texture analyses, the recognition rate of morphologically similar objects can be improved compared to the use of either one alone [16], being illustrative on how SHATE could solve ambiguities.
  - In neuroscience, multi-modality fusion networks combining statistics derived from spatial geometry with features from CNN significantly improve prediction over single-stream networks [18].
  - In the field of botany and paleontology we have studied leaf identity, where it is shown that classification can be improved by fusing outline-based features with texture-based CNN features for intermediate traits that are shared among cryptic taxa [17].
- For example, in medical imaging advanced fusion (e.g. wavelet and transformer-based) methods have been shown to enhance multimodal segmentation and classification performance, highlighting the practical feasibility of sophisticated fusion models in decision critical situations [17].

In sum, the case studies encourage a Raja-centric fusion approach, which utilizes feature-level fusion to capitalize on interactions between shape (GMM) and texture/pattern (DL), with attention mechanisms to adaptively weight modality contributions based on specimen state [16].

5.4 A Proposed Fusion Architecture for Raja

A practical, scalable fusion architecture tailored for Raja taxonomy includes the following components:

- **Input**: A standardized dorsal photograph of the skate (with controlled lighting and scale references to support reliable landmark detection) [14].
- **Module A (Shape)**: An automated landmark detection system (e.g., heatmap regression network) identifies key landmarks; a geometric encoder converts these into a Shape Vector embodying Procrustes-informed shape descriptors.
- **Module B (Texture)**: A CNN backbone (e.g., ResNet50) processes the image to extract a Texture Vector from a specified feature layeRaja
- **Fusion:** A Fusion Block utilizes attention mechanisms to dynamically weight shape and texture contributions, allowing the model to prioritize the more informative modality for a given specimen. Attention-based fusion leverages techniques shown to enhance performance across a variety of domains [19].
- **Output:** A probabilistic species distribution with interpretability overlays (e.g., Grad-CAM visualizations) to show the decision influences of shape or texture, supporting explainable taxonomy [14].

- **Explainability and Auditability:** Incorporating Grad-CAM or similar saliency mapping helps to visualize the CNN's focus on texture/pattern while displaying shape-related decisions through landmark deformations. Explainable AI (XAI) is crucial for fostering trust in fisheries management applications [14].
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Such fusion architecture comes under the direction of known multimodal learning best practices and has found evidence successes in cross-domain applications showing benefits of integrating shape and texture representations in an effective manner. The proposed methodology will also be designed taking into account deployment-oriented features, like light-weight attention modules for on-board surveillance systems that can still achieve good performance [20].

Practical Deployment and Interpretability:

- Data quality and standardization are paramount. Consistent image acquisition protocols that mitigate parallax, ensure scale references, and standardize lighting will enhance landmark accuracy and texture discrimination, improving fusion performance [14].
- Explainability remains essential for acceptance in policy and fisheries management contexts. Techniques like Grad-CAM can assure the model's decisions align with biologically relevant cues [14].
- Addressing data scarcity may involve employing transfer learning and data augmentation strategies. Pretrained CNN backbones on large datasets can accelerate texture learning for Raja images, alongside domain-specific fine-tuning and augmentation to balance class representations [15].
- Evaluation should use held-out catch data reflecting the ontogeny, lighting, and imaging conditions typical of field scenarios, with standard metrics (precision, recall, F1-score) reported alongside qualitative interpretability analyses.

5. Implementation Challenges and Practical Workflows

Bringing those GMM–DL's to fruition in tools for operations fishery management has a whole lot of challenges that very much have to be passed. Below I address the discussion under each established subheading, with supporting evidence integrated from key empirical and methodological literature contained in this reference pool.

6.1 Data Acquisition and Standardization

Quality of data is the foundation for inference in automatic taxonomy. The adage "garbage in, garbage out" is particularly applicable when the signal (morphology) is confounded by noise (lighting, occlusion, deformation) as well as by the bringing two master's together: GMM and DL pipelines.

- **In-situ and laboratory image quality:** Real-world acquisition GAN-based transfer of the knowledge on 2D images acquired in standard conditions (namely clear water, regular light and non-disturbing human presence) to in situ scenarios characterized by a high degree of variability in terms of lighting, turbidity, partial occlusion and acquisition poses. For multimodal learning and explainable AI frameworks, they highlight the significance of training data reflecting operational context, or else domain shift would cause model degradation [15]. Corrupting the training set with in-situ noise and occlusion enhances robustness of both the DL texture/appearance stream, and also, re-training with corrupted landmarks using GMM landmark stream [15]. For Raja, deployments on systems like Deep Vision or other on-board cameras will be designed along with data collection campaigns intentionally spanning the lighting regime and motion blur to capture realistic distributional shift [15].
- **Data management and provenance:** Metadata that needs to be standardized (i.e. the camera configuration, distance, scale bar reference at microlevel; the condition of the samples/reason for preservation in case of larger specimens and if appreciable any norming imaging files related parameters) is key to ensure reproducibility as well as cross study comparisons of results between different studies. The multimodal machine learning literature highlights the need for consistent data origin across modalities to achieve successful fusion [15]. The taxonomic morphometrics also find support in detailing the conditions of acquisition from which Procrustes coordinates are estimated [10].
- **Validation under field conditions:** To facilitate the robust implementation, models need to be tested on independently held field data that reflect operational settings (in-net or dockside) prior to use for management. The Grad-CAM and similar XAI algorithms can be useful in validation steps, showing that the model is attending to biologically meaningful features (e.g., buckler thorns on Raja clavata, marginal white spots on Raja brachyura), rather than background information/artefacts: it may enhance trust and help error diagnosis [14]. Explanations by Grad-CAM have been effective in verifying model decisions in various domains, suggesting that they could be applied to Raja images as well [14].
- **Practical takeaway:** A disciplined data pipeline for Raja would (i) promote a standardized imaging protocol across both dorsal and ventral views, (ii) curate lab-quality and in-situ images to span the space of pose, light and occlusion, (iii) provide careful landmark annotation, with semi landmarks if possible, (iv) include metadata that reveals origin of each image upon inquiry; At model validation time embed XAI checks by ad-hoc attention analysis.

6.2 Class Imbalance and Rare Species

Fisheries data is of a clear heavy long-tails, with common species making up the bulk of observation values while rare or protected taxon's are infrequent. This imbalance is a difficulty for DL learners and, therefore the GMM–DL fused system.

- **The problem in Raja context.** In the case of commercial landings, depending on their respective cryptic lineage within the Raja miraletus complex or rare species like populations belonging to Raja undulata, abundances of Raja clavata or Raja montagui may surpass that release those. knowledge, with many (in systematics suggests that species that are widely found among sympatric species consist of numerous cryptic microspecies restricted to small ranges and difficult to detect using traditional survey techniques 1. Such patterns are informative for Raja: an imbalanced training dataset could lead the model to bias towards dominant taxa and return overconfident misclassifications on rare lines.
- **Mitigation strategies.** Data augmentation is a common solution in DL for imbalanced datasets such as image transformations (rotation, flipping, color jitter etc.) to extend the representations of minority classes and other advanced techniques like synthetic data to balance the training samples [22]. More generally, in the pursuit of interpretability, interpretable AI pipelines can determine when minority-class decisions are based on irrelevant cues that favor a certain bias, leading to targeted data acquisition for debiasing [23]. Multimodal learning architectures also enable re-weighting or re-balancing mechanisms using complementary cues from shape (GMM) and texture (DL) streams to regularize predictions in scenarios with few minority-class samples [15].
- **Contribution of synthetic data and domain-adapted augmentation:** Although generative methods such as GANs have been shown to be promising for balanced dataset generation across different domains, the implementation of Raja-specific GAN is still under active development. However, the underlying justification—artificial samples ie that reasonably extend underrepresented morphologies—but they could be used to inform Raja in future work, particularly when coupled with domain-specific constraints from landmark geometry. The literature on interpretability highlights the need to assess quality of synthetic data and its influence on downstream decision-making, with explainability tools (e.g., Grad-CAM) helping diagnose whether synthetics meaningfully contribute discriminatory information or introduce artefacts [21][24].
- **Practical takeaway:** Further reducing class imbalance in Raja taxonomy should include (i) principled data augmentation for minority morphotypes (ii) continuing curation of additional real-world samples from under-sampled lineages; and (iii) continuous application of XAI in game-play monitoring against use of spurious cues. This trio enables enhanced performance along ontogenetic stages, color morphs and cryptic lineages, decreasing the chance of systematic misclassification in fisheries processing pipelines [15][17].

6.3 Explainable AI (XAI)

A luxury, or a necessity Policy decisions and management should not be informed by automated tools. XAI approaches yield human-interpretable explanations on model predictions making their validation, oversight and transparent governance possible.

- **Core XAI mechanisms.** Grad-CAM family and alike produce spatial heatmaps which indicate the image regions most responsible for a model's decision, providing an immediate tool to check whether a model is attending to taxonomically relevant features (e.g., thorn texture, marginal spots and disc contour) as opposed to background motifs. Grad-CAM is defined as a generic architecture-agnostic solution for gradient based visual explanation in wide range of domains with very few open parameters [14]. Recent work has demonstrated how Grad-CAM and SHAP-style explanations can be useful not only for auditing model behavior, but also in communicating decisions to non-experts or driving data collection/model refinement Zhang & Ogasawara [21][22].
- **Practical use of XAI in Raja networked pipelines:** In fusion systems as the threat focused on Raja, Grad-CAM heatmaps can be exploited to (i) confirm texture-based discriminants (e.g., dermal denticles, thorn distribution), and (ii) confirm shape-based cues (e.g., snout length, disc margins) encoded by the GMM module. A comprehensive XAI process might further involve the attention maps from feature-level fusion networks to show where and how differently the model computes shape and texture for various specimens which in turn would assist in focused enhancements, stakeholder trust [14].
- **Auditing and governance implications:** Interpretability research demonstrates the critical need for transparent reporting and model auditing, coming to management when AI-supported decision-making received is introduced into management circles – policy intelligence as well as interpretability:81. A review on interpretability in healthcare (a representative high-stakes decision domain) has identified taxonomies, tools and best practices that are also applicable to conservation and fisheries (e.g., Grad-CAM, SHAP and related approaches) [23]. The literature also warns us not to depend on any single explanation approach too much and instead recommends "multi-modality" [27] of explanation methods following the evidence in a similar way to that which could support validity of a model (triangulation). [21].

6.4 Practical Validation Metrics

A test of true performance would be for strong validation data in terms of the standard DL criteria (e.g., held-out color morphen, ontogenetic stage variation, and if possible, geographic subpopulations).

- **Metrics:** Calculation of confusion matrices, precision, recall, F1-scores and overall accuracy is crucial for measuring discrimination between species and cryptic lineages. The case-study like DL reporting in cross-domain imaging tasks show the informativeness of these measures for diagnosing class specific performance and comparison between unimodal versus fusion strategies [22]. Furthermore, diagnostics derived through XAI (e.g., Grad-CAM heatmaps) should be integrated with quantitative metrics showing that high performance is steered by actual, biologically valid cues and not dataset-specific biases [21].
- **Validation strategy:** Perform stratified k-fold cross-validation across taxonomically informed splits (e.g., species, ontogenetic stage and where possible geography) to evaluate generalization. Independent field validation employing dockside or net-side imagery would

represent the final test of deployment readiness, with performance monitored over time to detect drift in appearance resulting from seasonal or geographic difference [16].

Broader Implications for Conservation and Policy

The development of automated Raja discrimination systems has implications for conservation, fisheries management and policy. Here I discuss three specific realms in which automatic shape–vision fusion can lead to concrete and tangible improvements, while drawing evidence from the cross-lands literature on cryptic diversity, molecular taxonomy and AI explainability.

7.1 Improving Stock Assessment

- **Rationale.** Conventional skate stock assessments have frequently been based on pooled landings data that obscured species-specific demographics. Discriminatory, automation-enabled workflows would provide opportunities to de-aggregate catch by species and cryptic lineages, resulting in species-specific stock assessments (and consequently TACs) and better alignment of management structure with biological reality. Studies on cryptic diversity have highlighted the existence of divergent cryptic lineages with divergent spatial and ecological niches and thus demonstrating that resolving taxonomic identity is important for stock assessment and conservation management [1]. This resolution is of great importance in Raja due to morphological crypticity and lineage divergence within complexes such as that of Raja miraletus, which was shown to be composed by several cryptic lineages with different distributions [1].
- **Empirical precedent and methodological support.** Molecular and morphometric analyses have exposed cryptic diversity in Raja and related taxa, complementing species delimitation and management strategies-guidance units [1]. Multimodal automation integrating GMM and DL can translate these insights at a large scale, facilitating routine, reliable species-specific catch reporting and stock modeling [15][25].
- **Policy and practice implications:** If confirmed for field deployments, automated discrimination might underpin regulatory frameworks that mandate species-specific landings reporting and bycatch mitigation plans, thereby affording a greater level of protection to cryptic or slow-growing Raja taxa while permitting sustainable exploitation of more robust congeners [1].

7.2 Combating Seafood Fraud

- **Rationale:** Market mislabeling remains an issue in seafood supply chains and could mask the actual species' composition among skates that are landed. In Raja cases, misidentification may undermine protections for sensitive species and mischaracterize stock status. An identification pipeline based on matching of fusion images may enhance traceability and to a greater extent enforceability by enabling image-based [1] species assignment during dockside or processing.
- **Technological synergy:** GMM can offer a stable shape description across different images with difference in lighting and DL can utilize texture/pattern cues (the thorns, dermal denticles and spot distributions), which are less affected by variation in lighting etc., to separate visually very similar species from a noisy image. XAI modules (Grad-CAM, SHAP) provide clarity for decision justification to inspectors, managers and policy makers increasing trust and adoption in regulatory [21].
- **Empirical anchors:** Such cryptic diversity research highlights the danger that a morphology-based key alone may be identifying individuals incorrectly, especially when color morphs or ontogenetic stages mix up diagnostic characters. The DL texture analysis combined with GMM shape descriptors offer a more solid framework for labelling of claims in supply chains and the validation of the declared species presence in fish markets [1].

7.3 Unmasking Cryptic Extinction

- **Rationale:** Cryptic extinction is the term adopted here to describe those losses [4][5] of genetically or morphologically cryptic lineages that are not apparent based on external morphology or the set of survey characteristics used to quantify both described and undescribed species. The capacity to detect cryptic diversity and track its dynamics through automated recognition within catches presents a strong early-warning signal for conservation intervention. Cryptic diversity may differ in distribution and demography even when morphological change is minimal, the literature on cryptic diversity emphasizes, highlighting the importance of sensitive and robust methods to monitor lineages [1][4].
- **Practical utility:** A unified GMM–DL pipeline propagated to landing sites would be able to identify changes in the relative frequency of morphologically cryptic Raja lineages through time, highlighting potential cryptic extinction dynamics. This is consistent with a general trend where cryptic diversity mirrors ecological niche divergence and geographic structuring, so that strategic conservation decisions could avoid irreparable losses [1].
- **Cross-domain corroboration:** The overall trend of cryptic diversity among taxa cryptic lineages viable in distinct ecological or geographic settings is evident from molecular and morphometric studies in both aquatic and terrestrial systems. This conclusion is obvious for Raja: taxonomic resolution is an essential requirement to identify and ameliorate cryptic extinction trajectories [1][2].

Conclusion

The genus Raja is the intersection between a biological emergency and technological transformation. That same general-purpose morphology which enabled skates to be so successful for millions of years became a liability in the modern era of industrial fishing and lousy taxonomy. The "taxonomic impediment," including an ability to impossible to separate the cryptic from the common, often junior or regional variant from the species, undermines population sustainability.

This paper has shown that the answer lies in interdisciplinary synthesis. Geometric Morphometrics offers the precise yet interpretable methodology for quantifying minute shape differences between lineages. Deep Learning provides the primitive perceptual power that is required to read the complex textures and patterns that define persons. It is the mashup of these two methodologies that provides (drum roll, please) a "Digital Taxonomy" that is Nuanced, Scalable and Superhuman in consistency.

There are obstacles to using these elements. It involves building high-quality, genetically verified reference libraries (as part of integrative taxonomy), standardizing imaging protocols, and providing explainable AI interfaces that can translate the computer scientist, and the fisheries manage Raja. We conclude by interpreting what success would mean for digital FAMS: accurate stock assessments, preservation of cryptic biodiversity and sustainable exploitation for our oceans making it worthwhile to work towards this goal. However, by revealing the cryptic diversity of the Raja, we don't merely identify them; we rescue them.

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