GPT Vision Meets Taxonomy: A Comprehensive Evaluation for Biological Image Classification

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Abstract This study assesses the proficiency of GPT Vision, a multimodal language model, in the classification of biological images across taxonomic ranks. Utilizing a meticulously curated dataset from A–Z Animals, Wikipedia, and eLife Sciences, the model's performance was analyzed at various levels from Phylum to Species. Our quantitative analysis, supported by Python libraries like Pandas, Matplotlib, Seaborn, SciPy, and Statsmodels, revealed a trend of high accuracy at broader taxonomic categories, with a notable decrease at more specific levels. The overall accuracy peaked at 78.95% for Phylum but dropped to 11.58% for Species. Misclassification and null value analyses were conducted, indicating both the strengths of GPT Vision in identifying certain taxa and its limitations, especially at narrower taxonomic levels. The findings underscore the potential of GPT Vision in biological classification while highlighting the necessity for further model refinement, particularly for lower taxonomic ranks.

Keywords GPT4 · GPT vision · Biological image classification

1 Introduction

1.1 Background on Image Classification in Biology

Image classification plays a pivotal role in a multitude of disciplines within the field of biology, encompassing genomics, computational biology, medical diagnoses, drug discovery, biodiversity conservation, and ecological studies [1–3]. Automated, image-based high-content screening serves as an essential tool for exploration in

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the realm of biological science [4]. When it comes to the analysis of biological images, the classification of datasets is frequently executed employing specialized techniques such as deep learning and convolutional neural networks (CNNs) [5]. These techniques have demonstrated remarkable progress in the realm of image-based classification, recognition, and detection tasks [6]. Furthermore, the utilization of parallel neural networks and rule-based genetic algorithms has been investigated for the purpose of image classification in biology "(Binary Image Classification using Parallel Neural Networks", 2020; Tseng et al. 2008).

To achieve precise image classification, a variety of methodologies and characteristics are employed. For example, the proposal of combining multiple characteristics and utilizing random subspace classifier ensembles has been made for the purpose of phenotype recognition [6]. Moreover, the utilization of indicator kriging error comparison and texture analysis has been implemented to identify specific regions within intricate intracellular spaces [6]. In the domain of stem cell research, image analysis techniques have been employed to identify tenogenic differentiation using Convolutional Neural Networks (CNNs) [6]. Furthermore, the assessment of colony and nuclear morphology has been utilized to evaluate human induced pluripotent stem cells [8].

In the context of animal taxonomy, automated image analysis techniques have proven to be valuable tools for species identification and classification. These techniques involve image processing and the extraction of relevant features from specimens' images, followed by the classification of these features into correct categories. By utilizing automated image analysis, scientists can streamline the process of species identification, saving time, and resources [9].

The emergence of automated recognition algorithms exhibited a considerable degree of precision in the identification of plant species in the geographical region of Northern Europe. These algorithms take into consideration diverse image characteristics, including plant organs, background composition, and the concentration of species being analyzed [10]. Furthermore, the quantity of training images accessible for particular species influences the effectiveness of the automated recognition algorithm (Pärtel et al. 2021). This clearly exemplifies the potential of employing automated image analysis techniques to accurately discern and categorize various plant species.

1.2 The Advent of Machine Learning and Its Implications for Biological Image Classification

The advent of machine learning has had significant implications for biological image classification. Machine-learning algorithms have shown great potential in analyzing large and complex biological data [11]. The application of machine learning to biological image processing has expanded with the development of deep-learning techniques [12]. These techniques have enabled the automated analysis of biological images, leading to high-throughput measurement, identification, and sorting of biological entities [13].

However, there are challenges in applying machine learning to biological image classification. Variations in cell densities and differences in low-level image features can compromise the reliability of machine-learning methods [14]. Additionally, the availability of data and the rarity of certain diseases can impede the application of machine learning in musculoskeletal tumor imaging [15].

Despite the obstacles, machine learning has garnered significant acceptance in the realm of medical image analysis, specifically in endeavors such as image segmentation and classification, as stated by Dai et al. [16]. Furthermore, machine learning algorithms have demonstrated their efficacy in detecting latent pathologies in medical imaging, surpassing conventional image analysis techniques, as highlighted by Ayubcha et al. [17].

The field of animal taxonomy has been impacted by the advent of machine learning. Machine-learning algorithms have been utilized to aid in the classification and identification of animal species. By extracting features from specific image regions, machine-learning algorithms can classify these regions as either animal or non-animal [18]. This methodology has the potential to streamline the process of species identification and contribute to the overall understanding of animal taxonomy. Another such example is the app Merlin that specifically designed for Bird identification and classification.

1.3 GPT Vision's Potential in This Domain

GPT (generative pre-trained transformer) Vision's integration of vast internet-scale textual data with image processing capabilities holds considerable promise for biological image classification, particularly in the realm of animal taxonomy. Its hypothetical advantages in this domain are grounded in the following attributes:

Deep Contextual Understanding: The extensive scientific knowledge embedded in GPT Vision's training data can be used to provide context for visual features in biological images, potentially leading to more accurate classifications [19].

Advanced Feature Recognition: GPT Vision may excel at identifying subtle, species-specific visual cues that are critical for taxonomic classification due to its ability to access and process large datasets of biological imagery and their accompanying textual information [20].

Efficient Data Processing: The model's ability to rapidly analyze large numbers of images could support high-throughput classification tasks, potentially speeding up taxonomic workflows and research.

Continuous Learning: By utilizing reinforcement learning from human feedback, GPT Vision could iteratively improve its classification accuracy, adapting to new data and expert corrections over time.

1.4 Objective of the Study

The primary aim of this investigation is to scrutinize the efficacy of GPT Vision in the classification of biological images across various taxonomic levels. The study sets out to (1) quantify the model's accuracy and reliability, (2) understand its precision, (3) identify the taxonomic ranks at which the model excels or falters, and (4) highlight the model's behavior in the face of non-classifiable data. This inquiry strives to not only evaluate GPT Vision's current capabilities but also to pinpoint areas for potential enhancement, setting the stage for its application in the broader field of biological research.

2 Materials and Methods

2.1 Dataset Description

The dataset for this study was meticulously curated from a trio of reputable online sources known for their extensive biological repositories. The primary source was A–Z Animals (https://a-z-animals.com), a comprehensive database of animal images spanning a wide array of species. Additional images were sourced from Wikipedia (https://wikipedia.org), the renowned online encyclopedia that offers a vast collection of wildlife photography contributed by its global user base. Lastly, eLife Sciences (https://elifesciences.org) provided high-quality scientific images, supporting the dataset with a scholarly perspective.

Each image in the dataset was tagged with taxonomic information at multiple levels, ranging from the broadest category of Phylum to the most specific designation of Species. This multi-tier classification enabled a granular analysis of GPT Vision's classification capabilities, providing insights into its performance at each hierarchical level. The categorization process was underpinned by the taxonomic data available on the source websites, ensuring a scientifically grounded and accurate representation of biological diversity.

Categories and Taxonomic Levels: The dataset encompasses a diverse array of biological categories, reflecting the rich tapestry of life. These categories are organized according to the universally accepted biological classification system, spanning across several taxonomic levels. The broadest category included is the Phylum, which groups organisms based on fundamental body plans and structures. Within each Phylum, the images are further classified into Classes, Orders, Families, Genera, and ultimately, Species.

The Species level, being the most specific, denotes individual types of organisms that are capable of interbreeding, while Genus groups together species that are closely related. Family and Order represent higher levels of common characteristics, and Class groups together those orders sharing key attributes. The dataset, therefore, serves as a hierarchical map of biodiversity, capturing the complexity and nuances of biological classification.

By leveraging such a structured and comprehensive dataset, the study aims to dissect the performance of GPT Vision at each of these levels, delivering a thorough assessment of its classificatory acumen. This approach not only challenges the model across a spectrum of complexity but also mirrors the real-world application of such technology in the field of taxonomy and biological research.

As the GPT vision is available in easy-to-use chat interface inside ChatGPT plus, we input each image a simple initial prompt: "**I will give you some photos return me with only Phylum, Class, Order, Family, Genus and Species, if anything is not know just write NA for that taxon. OK?**".

2.2 GPT Vision Overview

GPT-4 V is a language model developed by OpenAI that incorporates additional modalities, such as image inputs, into large language models (LLMs). It is viewed by some as a key frontier in artificial intelligence research and development. The model enables users to instruct GPT-4 to analyze image inputs provided by the user, expanding the impact of language-only systems with novel interfaces and capabilities.

The training process for GPT-4 V was completed in 2022 and was the same as that for GPT-4, which is the technology behind the visual capabilities of GPT-4 V. The pre-trained model was first trained to predict the next word in a document, using a large dataset of text and image data from the Internet as well as licensed sources of data. The model architecture is not described in detail by the company (Open AI), but it is a multimodal language model that possesses the limitations and capabilities of both text and vision modalities.

After the pre-training, the model was fine-tuned with additional data using an algorithm called reinforcement learning from human feedback (RLHF). This algorithm produces outputs that are preferred by human trainers, allowing the model to learn from human feedback and improve its performance. The system card does not provide further details on the model architecture and training, but it does describe the safety evaluations, preparation, and mitigation work done specifically for image inputs [19, 20]. Figure 3 explains the whole process of the experiment visually.

2.3 Analysis and Visualization Techniques

The backbone of our evaluation rested on meticulous quantitative analysis, aimed at unraveling the nuances of GPT Vision's performance in biological image classification. To ensure precision and extract substantive conclusions, we utilized a selection of specialized Python libraries, each chosen for its specific capabilities in data analysis and visualization.

Pandas: Serving as the cornerstone of our data wrangling efforts, Pandas enabled us to meticulously clean, transform, and examine our data. It proved indispensable in structuring the image metadata and taxonomic classifications into organized data frames, which formed the basis for all further analysis.

Matplotlib and Seaborn: These visualization libraries were essential in bringing our data to life. Matplotlib offered a robust platform for crafting various plot types, while Seaborn, which extends Matplotlib, provided a means to produce more complex and visually appealing charts. These tools were pivotal in generating the bar plots, pie charts, and confusion matrix that elucidated GPT Vision's classification trends and challenges.

SciPy and Statsmodels: To delve deeper into the statistical aspects of our study, we utilized SciPy and Statsmodels. They facilitated the execution of advanced statistical tests, such as confusion matrices and accuracy calculations, to assess the reliability and precision of GPT Vision's predictions across the different taxonomic ranks. These analyses were critical in identifying the model's strengths and the areas requiring further training and optimization.

3 Results

Our study embarked on a comprehensive evaluation of GPT Vision's ability to classify biological images across different taxonomic levels. The results varied across the taxonomy, with the model exhibiting better performance at broader taxonomic levels and a decline as the classification became more specific.

3.1 Overall Accuracy Across Taxonomic Levels

To gain a deeper understanding of the model's strengths and areas for improvement, we computed analysis. In the presented Fig. 3, the classification accuracy of GPT Vision across different taxonomic levels is meticulously illustrated. Distinctively, two scenarios are compared: One where null values are incorporated (represented in blue) and another devoid of them (shown in red). At the broader levels of taxonomy, such as "Phylum" and "Class", the accuracy metrics are notably high, and there's a minimal disparity between the two scenarios. However, as we delve deeper into more specific taxonomic categories like "Order", "Family", "Genus", and "Species", a pronounced variability between the two conditions becomes evident. Particularly at the "Order" and "Genus" levels, the inclusion of null values appears to significantly diminish classification accuracy. Our results indicated that the model's performance, as measured by these metrics, mirrors the trend observed in the accuracy assessment, with higher scores at the Phylum level and a decline at more specific classifications.

This signifies that at lower level of taxonomy not only it unable to predict the taxon, it is more likely to predict wrongly.

The overall accuracy of GPT Vision's predictions across different taxonomic levels was assessed. The model demonstrated its highest accuracy at the Phylum level, with a success rate of 78.95%. As we traversed down the taxonomic hierarchy, the accuracy diminished, culminating at Species: 11.58% for Species identification (Fig. 1). Total accuracy with null values for Phylum level is, 78.95%, for Class: 61.05%, Order: 40.00%, Family: 26.32%, Genus: 20.00% and for Species it is 11.58%. The formulas to deliver the accuracy and to plot the bar chart in Fig. 3 is shown in Fig. 2. The Table below shows the exact numbers of correct, incorrect and Null Values (where GPT vision model denied to predict).

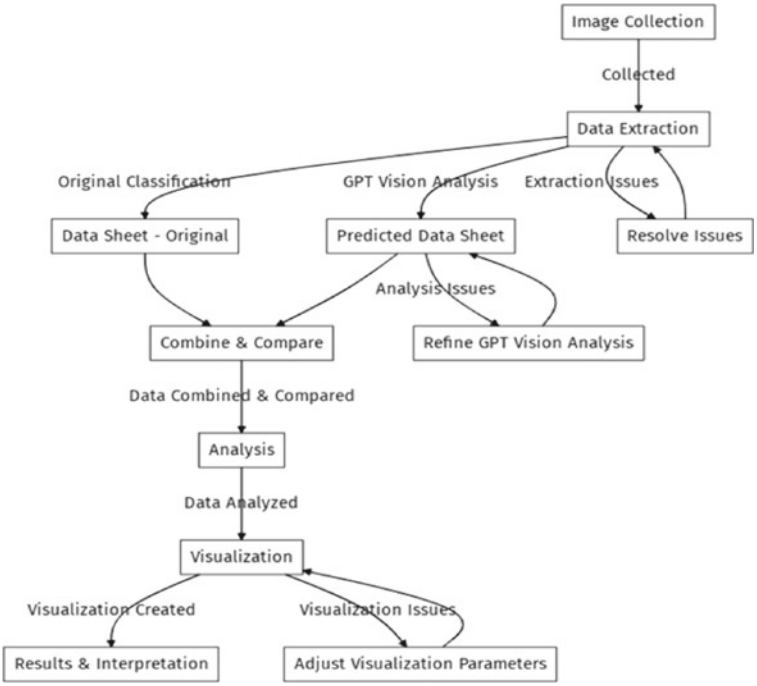

Fig. 1 Schematic diagram of getting the output and analysis

$$\text{Accuracy with null values} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Input}}$$

$$\text{Accuracy without null values} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of } Input - \text{Null outputs}}$$

Fig. 2 Formula to count accuracy with and without null values

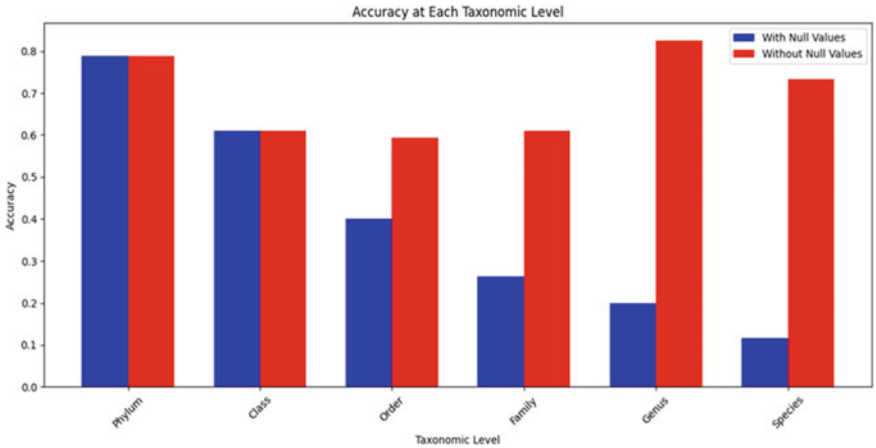

Fig. 3 Accuracy with and without recognizing null values (accuracies are in decimals should be multiplied with 100 to get percentage)

3.2 Detailed Performance Metrics

An examination of GPT Vision's predictions highlighted that the model occasionally failed to predict certain classifications, marking them as null. A pie chart analysis illuminated the proportion of predictions that the model could not classify versus those it did across different taxonomic levels Fig. 4.

In conclusion, our results shed light on GPT Vision's capabilities and potential areas for enhancement in the domain of biological image classification. The model exhibits commendable proficiency at broader taxonomic levels, with room for improvement at finer classification levels.

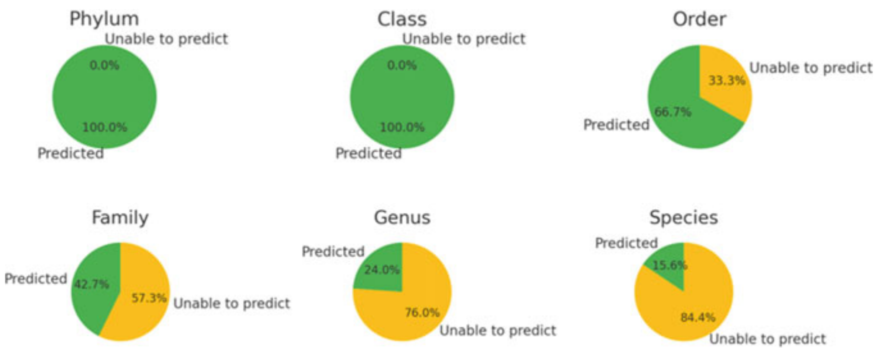

Fig. 4 Percentage of null values in each taxonomic level signifying models' denial to predict

Level	Correct	Incorrect	Null
Phylum	75	20	0
Class	58	37	0
Order	38	26	31
Family	25	16	54
Genus	19	4	72
Species	11	4	80

After a detailed examination of the provided diagram illustrating GPT Vision's performance on biological image classification, some intriguing patterns emerge. The phyla Mollusca and Nematoda stand out with consistently high accuracy rates across all taxonomic ranks, suggesting that GPT Vision adeptly identifies organisms within these groups irrespective of the taxonomic specificity. In contrast, the phyla Annelida and Cnidaria display significant discrepancies, particularly between the broader (e.g., phylum, class) and narrower (e.g., genus, species) taxonomic ranks (Fig. 5). And, the phyla Hemichordata showed a shocking zero accuracy mostly because of morphological similarity with annelida and mostly to the polychetae class. Such disparities in accuracy hint at the intricacies and potential challenges faced when differentiating between organisms that share close evolutionary ties or morphological similarities within these phyla. The data emphasizes GPT Vision's impressive capabilities in the realm of biological classification, but also pinpoints the domains that might benefit from more specialized training or fine-tuning.

3.3 Misclassification Analysis

Confusion matrix visualization was employed to depict the frequency of misclassifications at high taxonomic level. Our analysis revealed that certain taxa within the Phylum, Class, levels were recurrently misidentified, suggesting potential refinement. One platyhelminth image was misclassified as rotifera which is a phylum not even there in the whole sample (Figs. 6 and 7).

3.4 Data Availability Statement

Data Availability: All data and python code for data cleaning, exploration, accuracy count, and visualization are available in this Git Hub repository: https://github.com/Angsumi/GPT_VISION_FOR_Animal_Classification

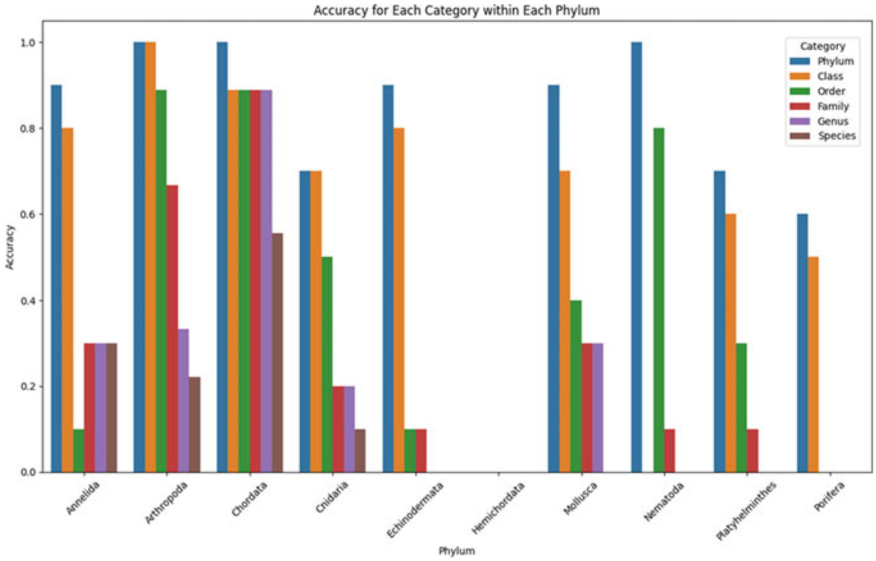

Fig. 5 Accuracy of each taxon within each unique phyla (Phlum Annelida, Nematoda, Arthropoda, Chordata, Cnidaria, Mollusca, Echinodermata, Platyhelminthes, Rotifera, Porifera are denoted as 0–9 successively)

4 Discussion

4.1 Interpretation of the Results

The analysis of GPT Vision's performance in biological image classification has yielded insights with significant implications for both the model's application and the broader field of machine learning in taxonomy. As observed in the results, the model's prediction accuracy diminishes as the taxonomic classification becomes more granular, with a notable decrease from broader categories such as Phylum to the more specific category of Species. This trend suggests that while GPT Vision is adept at discerning distinct, high-level biological features, its capability to differentiate finer taxonomic details is less robust.

However, an intriguing pattern emerges when null predictions—instances where GPT Vision abstained from making a prediction—are excluded from the analysis. The exclusion of these null values results in a marked increase in accuracy across the lower taxonomic levels. This observation points to a sophisticated aspect of the model's design; it appears that GPT Vision, likely due to the extensive and varied textual context inherent in its training, possesses an inherent caution in its predictive process. Rather than risking incorrect classifications, the model opts to withhold judgment when the available visual data does not suffice for a high-confidence prediction.

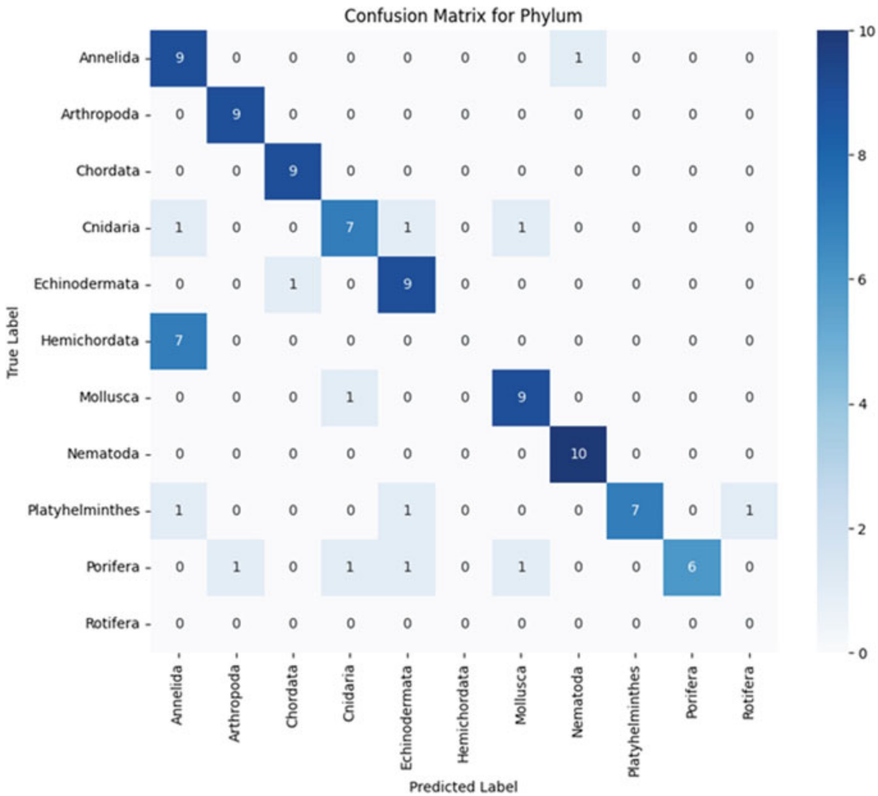

Fig. 6 Confusion matric of phylum level

This behavior may reflect a form of "artificial intuition", akin to a seasoned taxonomist who recognizes the limits of their expertise under conditions of uncertainty. From an academic standpoint, this self-regulating mechanism within GPT Vision's algorithm is a notable departure from the often-criticized "black box" nature of many machine learning models. It opens avenues for discussion on the integration of such models in scientific workflows, where the cost of misclassification can be high.

Further discussions could explore the implications of these findings for the deployment of machine learning models in critical fields. The self-awareness exhibited by GPT Vision in "knowing what it doesn't know" could lead to more reliable applications of AI in biological research and conservation efforts. It also raises questions about the training process for such models and the potential for incorporating explicit measures of uncertainty or confidence in their outputs.

Moreover, the findings stimulate a conversation about the balance between the breadth and depth of knowledge in machine learning applications. As machine learning continues to intersect with diverse domains, the ability of models to gauge their predictions' reliability becomes paramount. This study's insights into GPT

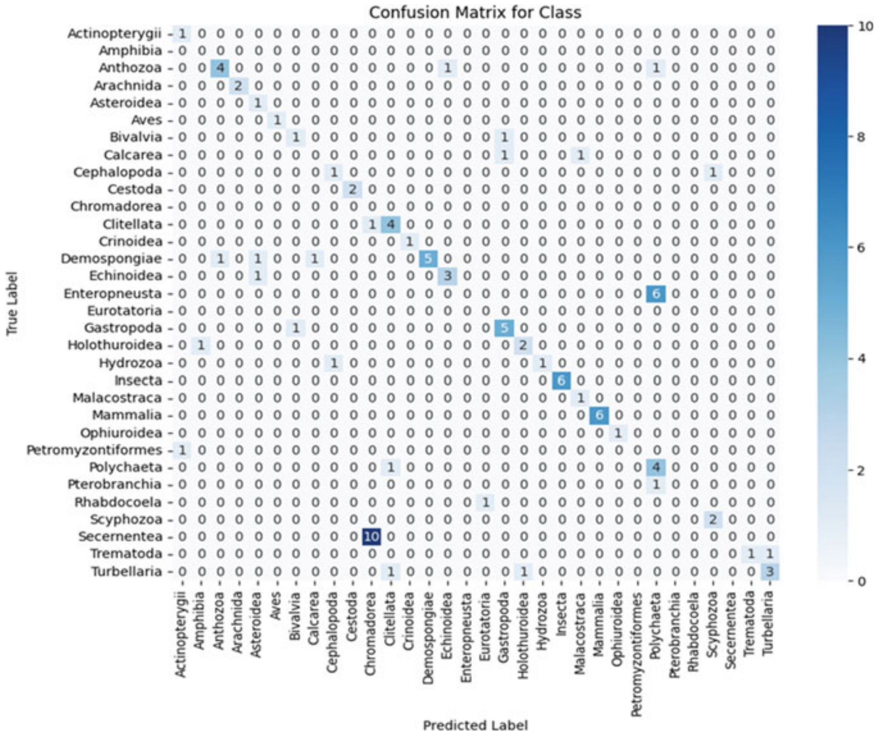

Fig. 7 Confusion matrix at class level

Vision's performance across taxonomic levels offer a valuable case study for such interdisciplinary dialogues.

4.2 Implications for Biological Research and Taxonomy

The potential of GPT Vision to revolutionize biological research through future enhancements is substantial. As the model's predictive accuracy at finer taxonomic levels improves, it could become an invaluable tool for rapid species identification, aiding in biodiversity monitoring and ecological studies. The model's cautious approach to classification, opting to provide no prediction rather than an incorrect one, sets a precedent for developing AI with a built-in safeguard against the propagation of errors.

Future iterations of GPT Vision could benefit from augmented datasets that include more varied and detailed images, coupled with robust metadata, enhancing the model's learning. Integrating feedback loops from taxonomic experts can refine its algorithms, enabling the model to approach the discernment of a seasoned biologist. With these advancements, GPT Vision may offer unprecedented support in cataloguing species, tracking invasive populations, and monitoring changes in biodiversity.

The implications for conservation biology are particularly promising. By automating the identification process, researchers can allocate more time to conservation efforts rather than the manual cataloguing of species. This increase in efficiency and accuracy, especially in remote or highly biodiverse regions, could accelerate conservation strategies and policymaking, ultimately contributing to the preservation of ecosystems on a global scale.

4.3 Limitations of the Study

This study, while expansive in its scope, is not without limitations. The dataset, though diverse, is limited to animal images and thus, the findings may not be entirely generalizable to plant species or microorganisms, which exhibit different visual characteristics and classification challenges. Additionally, the comparison with other models was beyond the ambit of this research, presenting an opportunity for future studies to benchmark GPT Vision against existing classification algorithms. The current assessment focused solely on GPT Vision's capabilities and did not explore a multimodel or ensemble approach that might yield improved results. These limitations underscore areas for further research, suggesting a broader application potential and inviting comparative analyses with alternative machine learning solutions.

5 Conclusion

5.1 Key Findings

GPT Vision demonstrates high accuracy in classifying images at broader taxonomic levels, particularly at the Phylum level, indicating robust recognition of general biological features. Accuracy declines at finer taxonomic resolutions, with the Species level showing the lowest accuracy, suggesting challenges in distinguishing subtle, species-specific traits. Excluding null predictions reveals an increase in accuracy, highlighting the model's ability to self-regulate and avoid overconfident, potentially incorrect classifications. The model's conservative approach in prediction mirrors the caution of expert taxonomists, indicating a sophisticated level of "artificial intuition" about its knowledge boundaries. Misclassification patterns, as visualized through confusion matrix, suggest specific areas where GPT Vision may require additional training or refinement. The study identifies a potential "artificial intuition" in GPT Vision's design, where it demonstrates a form of self-awareness in its predictive capabilities, a promising feature for AI applications in scientific fields. The research outlines the promise of GPT Vision's future application in biological research, with possible expansions into plant and microbial taxonomy, and its potential role in enhancing biodiversity monitoring and conservation strategies.

5.2 Recommendations for Further Research

Based on the study's findings and limitations, here are several recommendations for future research:

1. Algorithm Benchmarking: Benchmark GPT Vision against other state-of-the-art image classification algorithms, including convolutional neural networks (CNNs) and other machine-learning models, to contextualize its performance in the broader field of computer vision.
2. Artificial Intuition Exploration: Research the underlying mechanisms that enable the model's "artificial intuition", and how this can be further developed or refined to enhance decision-making in AI applications.
3. Cross-Domain Generalization Studies: Conduct research to test and improve GPT Vision's classification capabilities across different domains, such as plant species and microorganisms, to assess the model's generalizability beyond animal imagery.
4. Ensemble and Multi-Model Approaches: Explore the use of ensemble methods that combine GPT Vision's output with other models to see if accuracy at finer taxonomic levels can be improved. Investigate multi-model approaches that integrate GPT Vision with traditional ecological and genetic data to create a more holistic species identification system.
5. Interactive AI for Taxonomy: Develop interactive AI tools that can work alongside taxonomists, allowing for a human-in-the-loop approach to refine the model's predictions based on expert feedback.
6. Null Prediction Analysis: Analyze the circumstances and features associated with null predictions to better understand when and why the model chooses not to make a prediction, which could lead to more precise model tuning.
7. Understanding Misclassification: Undertake a thorough examination of misclassification patterns to identify any systematic biases or knowledge gaps in the model, which could inform targeted data augmentation and training strategies.

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