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AI Applications in Palaeontology: Enhancing Fossil Analysis and Interpretation

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Abstract

The proliferation of large datasets has facilitated data-driven approaches in paleontology, offering novel insights into evolutionary history. However, managing complex data poses challenges, including laborious processing and a lack of standardized evaluation metrics. Despite the widespread use of artificial intelligence (AI) in other scientific domains, its adoption in paleontology remains limited. This study reviews over 70 AI studies in paleontology since the 1980s, encompassing tasks such as micro- and macrofossil classification, image segmentation, and prediction. Various machine learning solutions, including Knowledge-Based Systems have been employed to automate paleontological workflows. The rise in AI adoption is attributed primarily to improved accessibility rather than advancements in fossil data or methodologies. Additionally, emerging AI implementations like diffusion models and the potential for Large Language Models is evident for future integration with paleontological research. Although AI has yet to become integral to paleontologists' toolkits, its successful implementation suggests transformative prospects for the field.

Keywords: Microfossils, Artificial intelligence, data-driven paleontology, machine learning.

1. Introduction

Artificial intelligence (AI) has recently surged in various disciplines within Earth sciences, revolutionizing them into data-driven studies. This transformation is evident in global hydrology, weather forecasting, seismology, remote sensing, and the carbon cycle. Despite these advancements, many earth science fields, including paleontology, have relied predominantly on manual workflows due to challenges in data collection, processing, and model suitability. Paleontology, focusing on ancient organisms through fossil records, has traditionally leaned towards "fossil-driven" studies. However, the rise of "data-driven" paleontological studies has marked a paradigm shift, enabled by large-scale datasets and advanced analytical techniques. These studies work with substantial fossil specimens and employ various methods to unveil patterns from data [1]. While the distinction between "fossil-driven" and "data-driven" studies may not always be clear-cut, the increasing availability of data and methodological advancements have propelled the rise of the latter paradigm.

Historically, notable paleontological studies like those by Matthew and Simpson laid early foundations for quantitative analysis of evolutionary trends. Later, the focus broadened to include marine biodiversity and major extinction events, providing insights into the co-evolution of life and environment. Methodological advancements, including numerical taxonomy and cladistics, facilitated quantitative

comparative morphological studies, enhancing our understanding of phenotypic evolution. Classic AI models and tasks have been instrumental in automating various paleontological analyses[2]. Early Knowledge-Based Systems (KBS) paved the way, although their adaptability and complexity were limited. Particularly deep learning, has since gained prominence, offering superior description and generalization abilities. Techniques like classification, segmentation, and prediction have been pivotal in AI applications to paleontological studies. For instance, the automation of stable isotope ratio and radiocarbon dating analyses for microfossils presents a significant challenge because of the requirement for a significant quantity of specimens. Recent developments in AI, particularly deep learning, offer promising solutions by enabling the accurate classification and collection of microfossils on a large scale. In this context, we introduce a system that integrates AI, digital image processing, and precise micromanipulation to accumulate a vast number of digital images of microfossils identified to the species level. This paper provides an overview of this system and presents the results of a practical test with radiolarian fossils, highlighting the potential of AI in advancing paleontological research.
This introduction sets the stage for understanding the evolution of AI-based paleontological studies, underscoring the significance of data-driven approaches in augmenting our understanding of Earth's history through fossil records.

2. Related Work

[1] Delivers a thorough examination of the application of artificial intelligence (AI) in paleontology, highlighting its potential for transformative effects on the field. It examines over 70 studies, focusing on tasks such as fossil classification and prediction, and discusses the challenges faced in data collection, processing, and the use of suitable models for complex paleontological data.
In terms of techniques and performance, various AI methodologies including Knowledge-Based Systems, neural networks, and machine learning methods are compared, analyzing their methods, datasets, and performance metrics. In the context of future prospects, the review indicates that although AI hasn't been extensively applied in palaeontology, its successful integration holds promise for substantial progress in the discipline. Additionally, the document delves into the application of machine learning specifically in paleontology, focusing on three key tasks: Classification studies delve into the utilization of AI models, specifically Convolutional Neural Networks (CNNs), for categorizing fossils. They delineate challenges like sparse data and the requirement for extensive, annotated datasets. Segmentation Techniques: The text details the use of AI for segmenting paleontological imaging data, traditionally a manual process, and highlights the time-saving potential of deep learning models. Predictive Modeling: It covers AI's role in predicting paleo-ecological behavior, such as mimicry in insects, using neural networks pre-trained on image datasets. Moreover, the discussion underscores problems related to data and model complexities, emphasizing the subjective nature of fossil data, the necessity for more advanced models, and the potential of new AI techniques in paleontology.
[2] The study introduces an innovative system for automated microfossil collection, leveraging artificial intelligence (AI) and a micromanipulator system. By automating the collection process, the system significantly reduces the time and effort required by technicians. Deep learning methods are utilized for microfossil classification, enabling accurate identification to the species level with over 90% accuracy. This capability facilitates efficient large-scale collection of microfossils. The practical application of this technology extends beyond microfossils, with potential uses in sorting various particles in fields such as medicine, food, and materials. The system consists of three integrated units: Image Collection,

Classification, and Particle Collection, coordinated through a communication program. This integration streamlines the process from identification to collection, enhancing efficiency and accuracy.
Overall, this innovative approach presents a promising solution for geochemical analysis and other applications that require precise particle sorting, showcasing the potential impact of AI-driven automation in scientific research and industrial processes.
An AI-driven system called miCRAD (microfossil Classification and Rapid Accumulation Device) is introduced, designed to streamline the process of microfossil analysis [3]. By utilizing a computer-controlled microscope and deep learning algorithms, miCRAD significantly expedites the identification and classification of microfossil species, while maintaining a high level of accuracy. Compared to manual analysis by experts, miCRAD demonstrates a threefold increase in efficiency, with consistent results exhibiting an error margin of less than 3.2%. This underscores the promising role of AI in paleoenvironmental research. Moreover the study proposes pathways for future endeavors in AI models to tackle more complex microfossil assemblages, indicating broader applications of AI within the field of earth sciences.

AI Study:

This section provides a comprehensive review of the evolution of AI applications in paleontology, spanning from the early 1980s to 2023. The studies are categorized based on their tasks, encompassing classification (both micro- and macrofossils), segmentation, and prediction.Despite the diverse origins of the organisms studied, the underlying methodologies and principles in research are often transferrable. The focus here is particularly on microfossil classification, which has been a focal point in paleontological AI endeavors, reflecting a rich history of applications. Microfossils, owing to their abundance and significance in various scientific fields such as evolutionary studies, sedimentary geology, and paleoclimate research, have been subject to extensive analysis. Unlike macrofossils, microfossils typically measure less than 1 mm and necessitate meticulous examination because of their diminutive size. They encompass a diverse array of tiny organisms including foraminifera, conodonts, coccoliths, plant pollens, and various fragments from other organisms, posing challenges in their recognition, identification, and classification. Historically, these tasks have required significant labour, leading researchers to explore automation through AI-driven approaches across various stages of the workflow, such as sampling, imaging, measurement, identification, and classification. Among these challenges, microfossil classification stands out as a fundamental hurdle, involving differentiation among similarly sized particles and classification into distinct species.
Early endeavours in this domain often employed Fourier analysis to discern patterns from outline shapes and other shape components critical for species identification or fossil recognition. Additionally, techniques like thresholding based on image pixel gray values were utilized for outline extraction from fossil images. However, these methods proved impractical under realistic conditions, often demanding extensive human intervention in data preparation or being confined to specific workflow steps. One prominent approach in early AI applications for microfossil classification involved knowledge-based systems (KBSs). These systems facilitated automated specimen identification and classification, leveraging established taxonomic hierarchies and anatomical terminologies akin to traditional paleontological keys. For instance, Swaby developed visual identification expert systems (VIDE) for fossil foraminifera and conodonts, integrating extensive image datasets and textual information [4]. Similarly, devised a dual-step identification system embedding a KBS and an image analysis subsystem, employing CLASSIC, a knowledge-based system shell.

However, despite their initial popularity, KBSs faced limitations, including reliance on expert knowledge, susceptibility to biases, and inability to handle unfamiliar objects. Moreover, their computational demands often resulted in prolonged identification times. Consequently, as probabilistic methods like random forest emerged, offering superior prediction capabilities with reduced design and maintenance efforts, the appeal of KBSs gradually waned. In contemporary AI studies, convolutional neural networks (CNNs) has gained prominence, particularly in the classification of both micro- and macrofossils. CNNs succeed in the process of learning intricate extracts characteristics directly from raw data, eliminating the need for manual feature extraction [5]. The ability to discern hierarchical patterns within images has revolutionized fossil classification, yielding remarkable accuracy and efficiency.

In essence, the progression of AI applications in paleontology, particularly concerning microfossil classification, illustrates a shift from initial knowledge-based systems to contemporary machine learning methods such as CNNs. This transformation highlights the ongoing pursuit of more effective and precise methodologies for analyzing fossil data, offering compelling possibilities for future research and exploration in the discipline. Fig1 and 2 are the samples on which machine learning models are developed to predict different types of Fossils.

3. Methodology

Microfossils, found within geological strata, play a crucial role in determining geological ages and conducting paleoenvironmental studies. However, their intricate structures make accurate identification a time-consuming task, requiring extensive expertise. With the increasing need to analyze large sample sizes, there's a growing concern regarding the scarcity of trained human resources in this field.

Artificial intelligence, specifically deep learning through Convolutional Neural Networks (CNNs), offers a promising approach to tackle the obstacles in microfossil classification. CNNs, modeled after the human brain, demonstrate proficiency in categorizing images following extensive training on extensive datasets. Unlike conventional machine learning techniques, CNNs autonomously extract pertinent features from intricate structures, rendering them highly suitable for microfossil classification.

Recent research have shown the efficacy of CNN-based techniques in microfossil classification. Mitra et al. showcased the ability of machine learning techniques based on CNNs to identify planktic foraminifera species with high accuracy (>80%). Similarly, Hsiang et al. developed the Endless Forams portal, comparing CNN-based classification results with human classifications, showing promising agreement [6]. Additionally, Marchant et al. reported good agreement between CNN-based classification of benthic foraminiferal assemblages and manual counts by humans. These studies highlight the effectiveness of deep learning approaches in microfossil classification tasks.

Recognizing the capability of CNNs in microfossil analysis, Itaki et al. developed the miCRAD (microfossil Classification and Rapid Accumulation Device) system. Comprising image collection, classification, and micromanipulation units, miCRAD utilizes a computer-controlled microscope/micromanipulator and deep learning methods for automated microfossil classification. This system provides fast image acquisition paired with precise classification, enabling non-experts to efficiently identify large volumes of microfossils.

To demonstrate the utility of the miCRAD system, Itaki et al. constructed classification models using transmitted light images to estimate the relative abundance of Cycladophora davisiana (%C. davisiana) in microfossil assemblages. By applying these models to actual down-core samples.

System Overview

The miCRAD system comprises of three units: Image Collection, Classification, and Particle Collection. The Image Collection Unit automates the acquisition of microscopic images of particles using a computer-controlled microscope, while the Classification Unit utilizes deep learning software to build classification models and identify particles based on acquired images. The Particle Collection Unit automatically picks up target particles determined by the classification results using a vacuum suction type micromanipulator. Advantages of CNNs in Microfossil Classification: CNNs offer several advantages in microfossil classification [7-9]. They remove the necessity for manual feature extraction, allowing for the automatic acquisition of relevant features. Directly from raw images. Transfer learning, a key methodological innovation, allows for the reuse of pre-trained models, reducing training costs and leveraging relevant information from existing datasets. Despite the initial effort required to generate high-quality training datasets, CNN-based models offer faster and more efficient microfossil classification compared to traditional methods like knowledge-based systems.

In summary, CNN-based approaches hold immense potential in revolutionizing microfossil classification, offering faster, more accurate, and efficient solutions to tackle the challenges faced in paleontological studies.

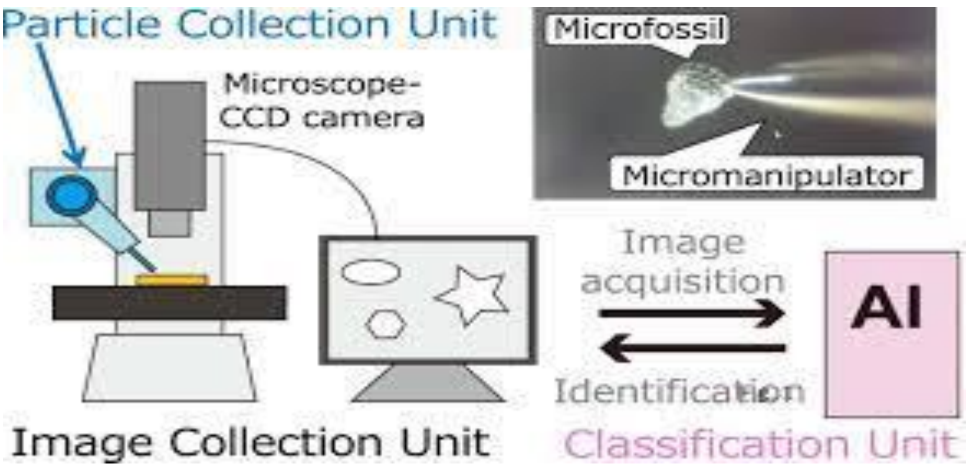

Fig1: Automated microfossil collection and classification [1]

4. AI-Driven Identification of Foraminifera and Dinoflagellates:

Foraminifera and dinoflagellates are pivotal microfossils in paleontological studies, offering critical insights into past environmental and climatic conditions. Traditionally, the identification of foraminifera species such as *Globotruncana arca*, *Globotruncana sp*., and *Gansserina gansseri* has been labor-intensive, requiring careful analysis of scanning electron microscope (SEM) images. However, artificial intelligence (AI) techniques, particularly convolutional neural networks (CNNs), have revolutionized this process, achieving over 90% accuracy in species identification by automatically recognizing distinctive morphological features, such as ribbing patterns, chamber arrangements, and apertural structures.

The light microscopic photographs in Plate 1 illustrate various dinoflagellate cysts from the DNG well "A" in the Krishna-Godavari Basin, India. These cysts, essential for paleoenvironmental reconstruction, display unique morphological characteristics that are often challenging to classify manually. The AI model used for dinoflagellate classification is designed to identify cyst morphology, surface texture, and spatial arrangement, making it possible to classify these species with high precision. The following species are identified in Plate 1:

Figures 1 and 2: *Areoligera coronata*, recognized by its smooth, rounded cyst with punctate features and prominent sutures.
Figure 3: *Areoligera senonensis*, distinguished by its slightly angular cysts and unique surface texture.
Figure 4: *Cerodinium diebelii*, featuring a more elongated cyst shape with distinctive longitudinal ridges.
Figure 5: *Cribroperidinium sp.*, showing a rounded shape with intricate perforations across its surface.
Figures 6 and 7: *Dinogymnium albertii*, characterized by an elongated cyst with well-defined processes.
Figures 8 and 9: *Heterosphaeridium latoaculeum*, displaying sharp, aculeate spines on the cyst surface.
Figure 10: *Heterosphaeridium spinaconjunctum*, with a similar spiny structure but more compact in shape.
Figure 11: *Heterosphaeridium sp.*, exhibiting variations in surface ornamentation.
Figure 12: *Nelsoniella aceras*, with distinctive surface features aiding in its classification.
By using AI, these dinoflagellate cysts can be accurately classified, streamlining the process and reducing reliance on manual expertise.

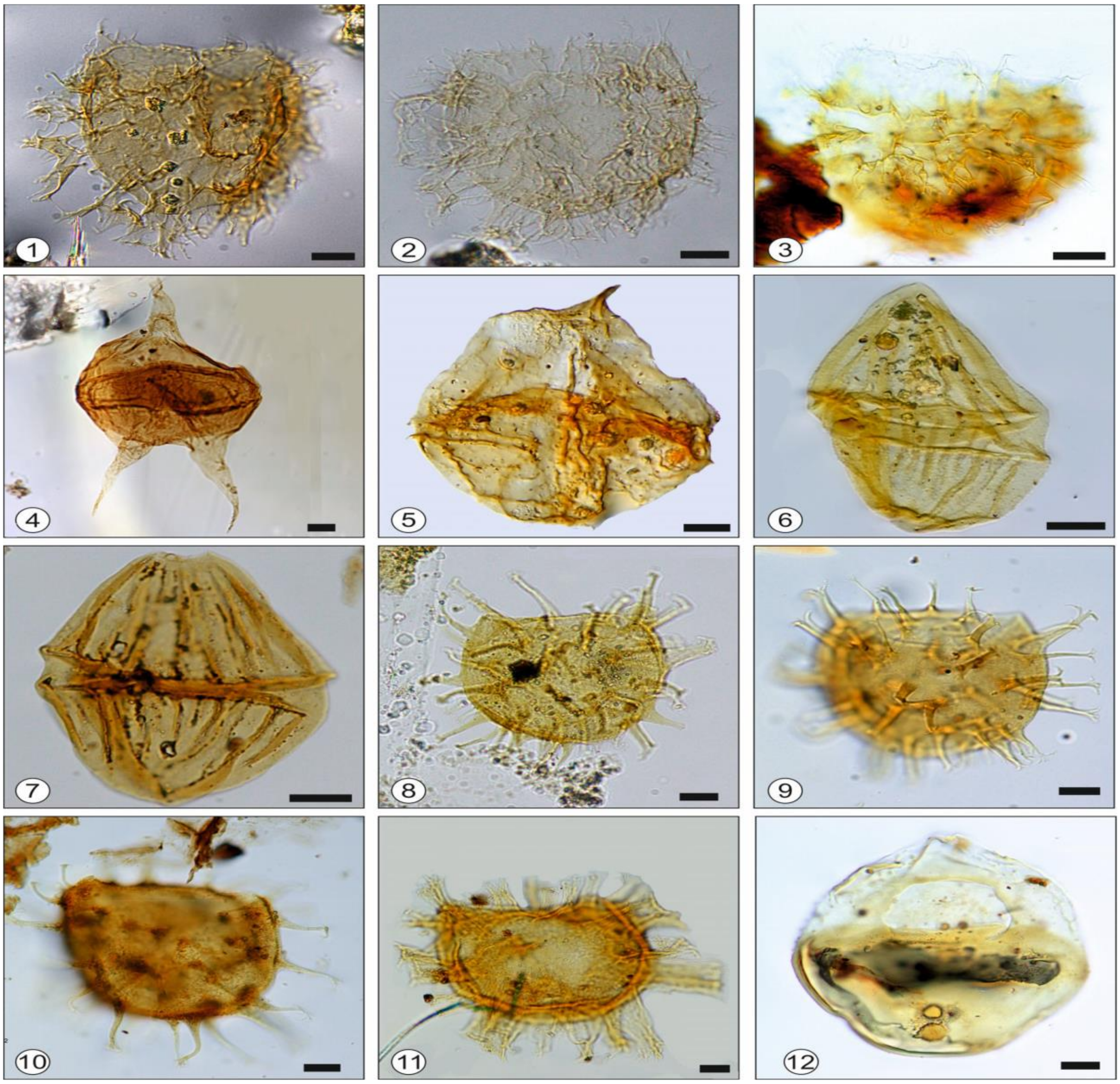

Plate1 (Figure1-12) Light microscopic photographs of dinoflagellate cysts from DNG well "A," Krishna-Godavari Basin, India. 1–2. *Areoligera coronata*, BSIP-16694, EFC-M15 (1), BSIP-16697, EFC-35N1 (2), 3. *Areoligera senonensis*, BSIP-16700, EFC-38Q, 4. *Cerodinium diebelii*, BSIP-16703, EFC-31G3,

5. *Cribroperidinium sp.*, BSIP-16697, EFC-54V2, 6–7. *Dinogymnium albertii*, BSIP-16698, EFC-36H4 (6), BSIP-16699, EFC-49D (7),8–9. *Heterosphaeridium latoaculeum*, BSIP-16700, EFC-48T (8), BSIP-16701, EFC-37F2 (9), 10. *Heterosphaeridium spinaconjunctum*, BSIP-16702, EFC-47E1, 11. *Heterosphaeridium* sp., BSIP-16701, EFC-24F3, 12. *Nelsoniella aceras*, BSIP-16705, EFC-48P3. Scale bars represent 10 µm and EFC represents England finder coordinates (After Ashish K. Mishra,2022 et al.,)

Moving on to Plate 2, the focus shifts to foraminifera species, continuing to highlight the effectiveness of AI-driven classification in paleontological studies. Plate 2 features the following foraminiferal species:

Figures 1-3: *Globotruncana arca* (Cushman, 1926), a species characterized by its biconvex test with distinct ribs. The AI model is particularly adept at identifying the spiral chamber arrangement and the clear ribbing patterns that define this species.

Figures 4-9: *Gansserina gansseri* (Bolli, 1951), displaying a planispiral form and intricate ornamentation. The model distinguishes the characteristic sutural structures and apertural features in this species.

Figures 5-6: *Globotruncana sp.,* an unidentified variant of Globotruncana species, showing subtle differences in chamber arrangement and surface features. AI can classify these more ambiguous forms with high precision by focusing on minute differences in chamber shape and surface texture.

The AI models trained on these foraminiferal species have demonstrated remarkable accuracy, automating the process of species classification by detecting specific chamber arrangements, ribbing patterns, and aperture locations.

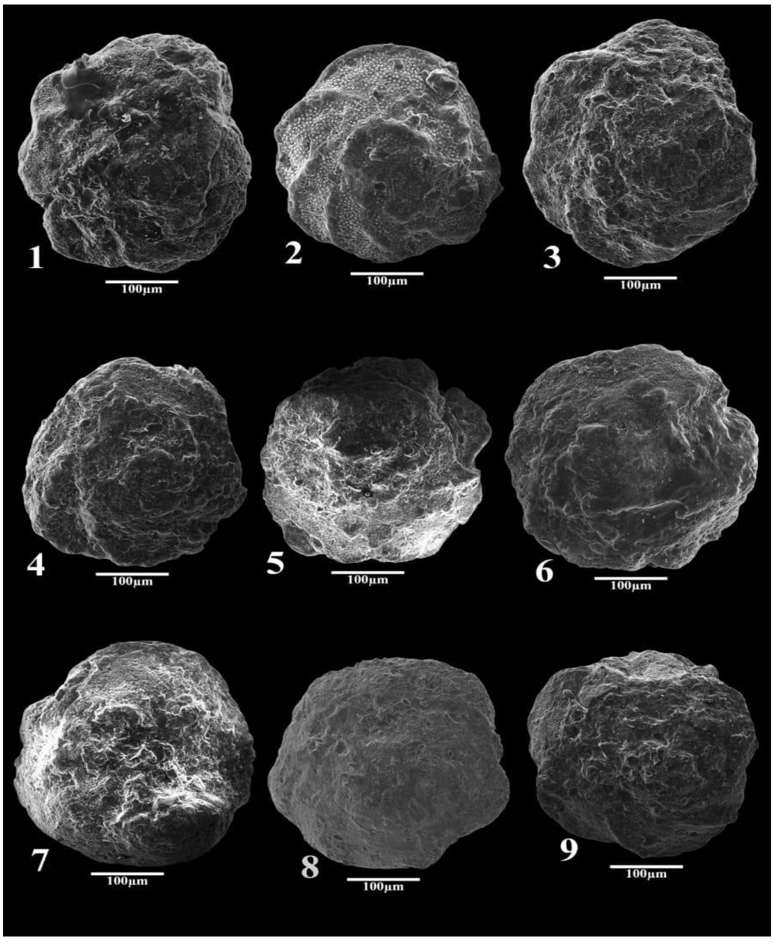

Plate-2: Fig1-3 *Globotruncana arca* , (Cushman, 1927), Fig 5-6 *Globotruncana sp* (5-6), Fig 4-9 *Gansserina gansseri* (Bolli, Loeblich, and Tappan, 1957).

Lastly, Plate 3 showcases additional foraminiferal species, further exemplifying the power of AI in analyzing complex microfossil records:
Figures 1 and 2: *Contusotruncana contuse* (Cushman, 1926), known for its robust, ridged shell and distinct central chamber. AI models can identify these features with high accuracy, even in fragmented specimens.
Figure 3: *Gansserina gansseri* (Bolli, 1951), identified by its planispiral shape and complex surface texture, features that are critical for classification.
Figures 4 and 7: *Globotruncana arca* (Cushman, 1926), which shows its typical biconvex shape with pronounced ribbing, a feature easily recognized by AI models.
Figure 5: *Globotruncana mariei* (Lehmann, 1947), which has a compressed, smooth test and reduced ribbing. The AI model effectively distinguishes this species based on the subtle differences in the chamber arrangement.
Figures 6, 8, and 9: *Globotruncana aegyptica* (Nakkady, 1950), characterized by its angular test and elaborate sutural structures. AI is particularly useful in identifying the detailed features of this species, especially in high-resolution SEM images.
With the use of AI, these foraminiferal species can be rapidly and accurately classified, reducing the time spent on manual identification and increasing the reliability of the classification process.

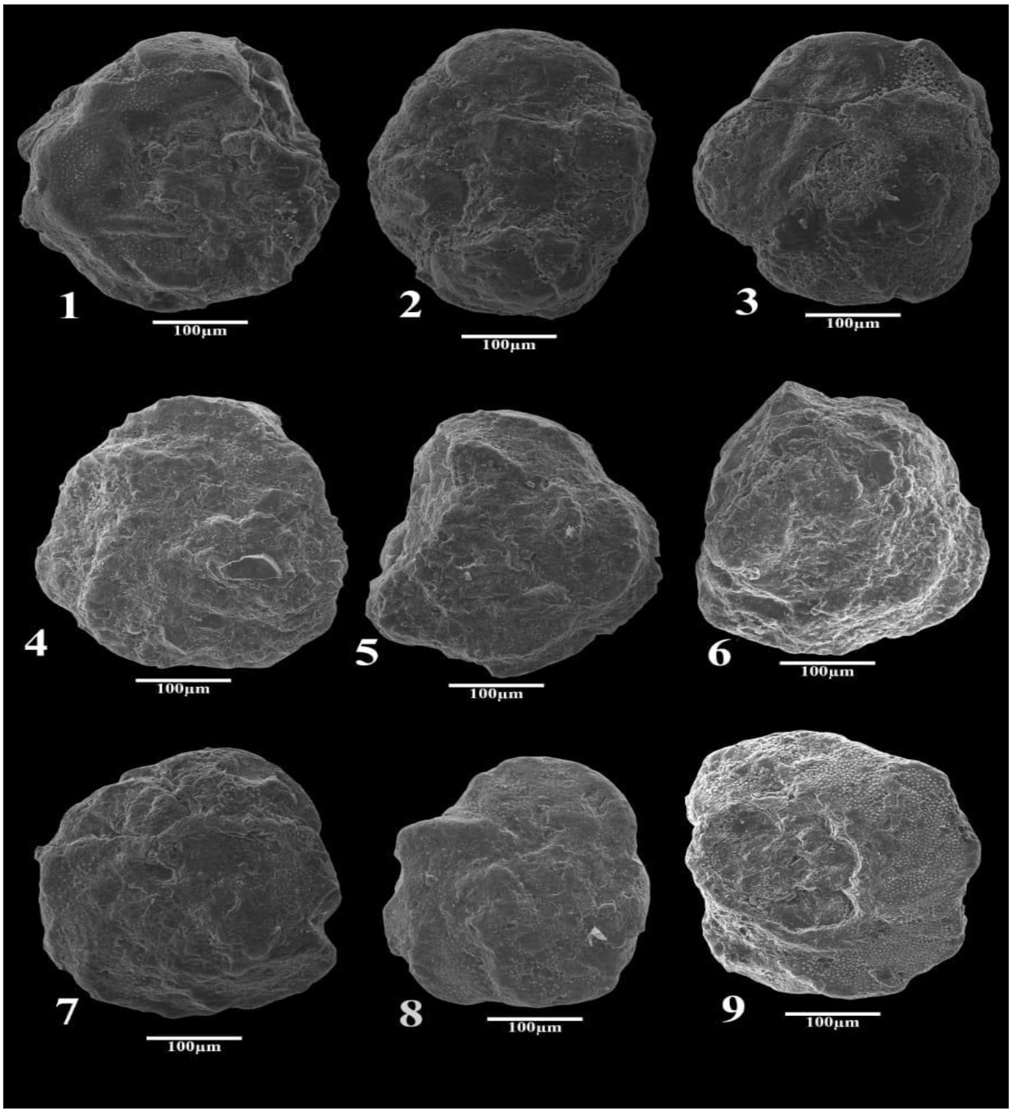

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Plate-3: Fig 1,2 *Contusotruncana contuse* (Cushman, 1938) , Fig 3 *Gansserina gansseri* (Bolli, Loeblich, and Tappan, 1957), Fig 4,7 *Globotruncana arca* (Cushman, 1927), Fig 5 *Globotruncana mariei* (Marie, 1941), Fig 6,8,9 *Globotruncana aegyptica* (Nakkady, 1950).

In conclusion, AI-driven techniques, particularly convolutional neural networks (CNNs), are transforming the study of both foraminifera and dinoflagellates in paleontology. These AI models enhance the speed and accuracy of species identification by automating the analysis of SEM and light microscopic images, enabling paleontologists to classify a wide range of species with high precision. This advancement streamlines the identification process, allowing for large-scale analyses of fossil records and offering the potential for new discoveries in the field of paleoclimatic and paleoenvironmental studies.

5. Analysis

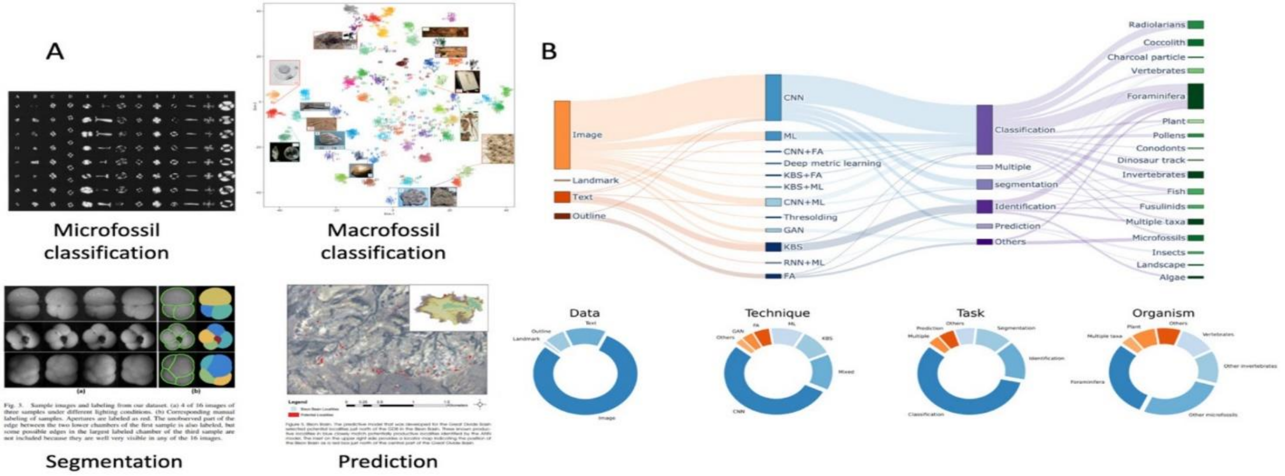

Image Collection Process: The miCRAD system enabled the gathering of images for both training and test datasets. Employing a CCD camera and image processing techniques, individual particle images were captured from a 36x24 mm cover glass. Around 5000 objects were extracted within approximately 10 minutes, with images clipped at a resolution of 280x280 pixels to ensure sufficient morphological characterization.

Fig2: A. Examples of paleontological AI tasks, images are modified from Dollfus and Beaufort (1999) Microfossil classification, Liu et al. (2023) Macrofossil classification, Ge et al. (2017) segmentation, and Anemone et al. (2011) prediction. B. proportions of taxa, methods, input data, and task in paleontological AI studies. Abbreviation: CNN, convolutional neural network; FA, Fourier analysis; GM, geometric morphometric; KBS, knowledge-based system; ML, machine learning [1]

Classification Model Construction: More than 75,000 individual images were grouped into five classes for training the classification models: "Cycladophora davisiana," "Cycladophora bicornis," "all other radiolarians," "centric diatoms," and "all other particles." Two CNN-based models, Cdv%v2 and Cdv%v6R, were constructed using these categories. The training dataset sizes for each category with each model. Testing and Classification Results: All test samples were collected using the miCRAD system and classified using the constructed models. Classifications were based on confidence values ranging from 0 to 1.00, with the highest confidence value used for assigning each object to one out of the five categories. The classification accuracy varied depending on the confidence level set. At a confidence level of 0.60, approximately 90% of objects were successfully classified, with accuracies for radiolarians, diatoms, and other particles exceeding 80% on average. However, the accuracy for C. davisiana ranged from 26.7% to 78.7%, indicating limitations in estimating its relative abundance under these model conditions [1].

At a higher confidence level of 0.95, the accuracy for C. davisiana improved, reaching 71.4% to 99.2% for model Cdv%v2 and 78.6% to 97.8% for model Cdv%v6R. Despite some samples showing relatively low accuracy for C. bicornis, the models were able to distinguish between species with similar structures. The accuracy for other radiolarians varied between 81.3% and 97.3% for Cdv%v2 and between 62.4% and 90.2% for Cdv%v6R[1].

Practical Test Results: Practical tests were conducted using model AI-PIC_20181024 on samples collected from both the Japan Sea and the Southern Ocean. Confidence levels were adjusted to optimize classification accuracy while minimizing the count of uncategorized images. For instance, at a confidence level of 0.60, the accuracy for both C. davisiana and A. boreale was 94% for sample U1422C. However, with higher confidence levels, accuracy improved while the count of categorized images decreased. The picking speed for identified particles was approximately 120 specimens per hour, with a success rate ranging between 70% and 80%.

Conclusion:

The development of an automated microfossil pick-up system incorporating AI technology represents a significant advancement in paleontological research. The practical test results confirm the efficacy of the classification model, AI-PIC_20181024, in accurately classifying microfossils at the species level, particularly for species like C. davisiana and A. boreale, with accuracies exceeding 90% at a confidence level of 0.90. However, there remains a challenge with a significant portion of images remaining uncategorized, particularly at lower confidence levels. To address this challenge and improve efficiency in microfossil collection, further refinement of the classification model is necessary. Ideally, the model should exhibit high accuracy even at lower confidence levels to minimize the count of uncategorized images while maintaining classification precision.

Moreover, the potential applications of this automated system extend beyond microfossil classification, with opportunities for adaptation in various industries such as mineral particle classification, steel manufacturing, agricultural seed sorting, food quality control, and medical diagnostics. Nonetheless, achieving successful integration of these applications will demand ongoing development efforts to seamlessly incorporate AI technology into microscope systems and customize the system to address the unique sorting requirements of individual industries. In conclusion, while the automated microfossil pick-up system and classification model show promise for revolutionizing paleontological research and finding applications in diverse industries, further refinement and development are essential to realize their full potential for practical use.

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