**The impact of Artificial Intelligence systems in Micropalaeontology**

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**Highlights**

Artificial neural networks and machine learning are potentially better at microfossil identification.

AI systems complement nuanced expertise from specialists.

AI systems are still in their infancy when it comes to becoming full experts in micropalaeontology.

**Abstract**

The discipline of micropalaeontology, fundamental in Geology, has witnessed substantial technological advancements in recent decades, aided by the exploitation of Artificial Intelligence (AI) systems to facilitate microfossil identification. This perspective paper explores the transformative role of AI in micropalaeontology, particularly in species identification, and its potential to help with the interpretation of microfossil assemblages. While it is argued that AI cannot fully replicate the expertise of a micropalaeontologist, an abundance of scientific studies shows the promising success of AI becoming adept at accurately identifying microfossil species.

**1. Introduction**

The discipline of micropalaeontology, one of the keystones of modern geology, has provided us with a wealth of information to enhance our understanding on the Earth’s evolution. From Herodotus, perhaps the first-ever micropalaeontologist to describe specimens of foraminifera, notably *Nummulites*, to machine learning techniques, this field has witnessed numerous technological innovations aimed at improving efficiency and cost-effectiveness.

One of the common issues that arises when studying microfossils (and even macrofossils) is the significant amount of time spent, not only on preparing samples to extract these fossilised organisms but also on identifying them at the highest taxonomical level. Nonetheless, this identification may not always be successful. The training of a micropalaeontologist relies on expertise, the time available and access to extensive academic resources and specialised instruments. Such facilities are not always readily available in academic institutions and may be becoming rarer due to a decline of funding in this discipline. Furthermore, there has been a steady decline in the number of micropalaeontologists, including palynologists, as our retired members are not necessarily replaced by a younger generation.

**2. Species identification: what are the challenges and solutions?**

The conventional way for identifying microfossils typically involves the use of microscopes (including stereoscopic, biological and scanning electron microscopes), written descriptions and atlases of photos, often compiled by researchers over time. Each group of microfossils presents its own set challenges, including the large number of species (from extinct to extant), morphological variability, poor preservation, taphonomy, and perhaps more challenging, the occurrence of cryptic species (species that are morphologically similar but with distinct genomes) (e.g., Darling et al. 2004).

With the advent of increased computational power in the 1980-90s, came the idea to develop methods to enhance efficiency and cost-effectiveness. One of the first attempt of automated counts (e.g., Swaby, 1992) marked the beginning of a fashionable (and still ongoing) movement, especially within the realm of oil exploration, as microfossils serve as key indicators of biostratigraphic and environmental conditions.

Foraminifera, one of the most common macrofossil groups used in palaeoenvironmental studies (such as palaeoceanography, biostratigraphy, and sea-level changes) were among the first organisms considered for identification using computer systems. These organisms are rather simple to extract from their depositional matrix. Due to their size and three-dimensional characteristics, it was relatively easy to develop computational systems that allowed both specialists and non-specialists to query potential identifications from databases. Over time, these systems were further refined to other microfossils as computers evolved in capacity and processing power.

My first interaction with such an online database was with the African Pollen Database developed in 1996 (<https://africanpollendatabase.ipsl.fr/#/home>), an invaluable tool that facilitated the identification of pollen grains based on their key characteristics.

Moving on a few decades, where do we stand today? Have the micropalaeontologists become an extinct species, replaced by various deep-learning models? Will AI become developed enough to provide an in-depth insight of the significance of fossil assemblages?

**3. Knowledge transfer from specialists to AI**

The traditional way of training micropalaeontologists typically involves access to reference materials, image atlases, diagnostic/taxonomical descriptions as well as training with experts. This process requires spending weeks, even months to gain confidence in the identification of specimens.

What does it take to train an AI? Convolutional neural networks (CNN) are artificial neural networks that utilise datasets of images to automate pattern recognition. This approach has been applied to various groups of microfossils. Dollfus and Beaufort (1999) pioneered the use of CNN for the automated recognition of coccoliths (SYRACO), which, after fine-tuning, achieved an impressive 96% accuracy in identifying 11 Pleistocene taxa. An inherent issue was the presence of the so-called invaders that resemble coccoliths; the authors circumvented this issue by estimating the percentage of the invaders in each microscopic field (Beaufort and Dollfus 2004).

However, upon reviewing the scientific literature since the inception of this technique, it appears that very few studies on coccolithophores have adopted it, with only eight peer-reviewed papers since 2004 (as per a Scopus search). This raises the question of what has been preventing wider participation in using CNN for coccolithophore studies, given that they are considered to be a major tracer of past environmental conditions and therefore a very valuable tool in palaeoceanography and biostratigraphy.

When examining the use of CNN in the study of other palaeoceanographical and/or biostratigraphic microfossils, there appears to be a more extensive application of this technique in foraminiferal studies. Indeed, this particular group of organisms is relatively straightforward to analyse in terms of sample preparation and microscopy observation compared to other groups such as palynomorphs. Their tests provide valuable insight into the biogeochemical conditions of our oceans, among other applications.

In recent decades, a relatively significant number of publications have highlighted the technical evolution of automated systems, ranging from isolated specimen acquisition (e.g., the Forabot system developed by Richmond et al. (2022) for planktonic foraminifera) to supervised machine learning approaches (e.g., Hsiang et al. 2019). Without delving into specific details, it must be noted that large databases comprising thousands of images are a prerequisite. However, they bring about several challenges, including resolution issues, specimen orientation as we are dealing with 3D objects, and variations in image processing settings between datasets created by different research teams (e.g., Tetard et al. 2023).

A consensus seems to be emerging from the application of Machine Learning, suggesting that the accuracy of species identification typically falls within the range of 80 to 90%. This level could be considered superior to human observation, as demonstrated by Mitra et al. (2019) in their study comparing the identification accuracy of 540 specimens of planktonic foraminifera among experts (63% accuracy), novices (53% accuracy) and CNNs (~80% accuracy). However, Al-Sabouni et al. (2018) have raised concerns regarding knowledge transfer, not only between researcher and automated systems but also among researchers themselves. Their findings emphasised the importance of training school for achieving consistency in identification. In addition, they noted that identification from real slides was 7% more accurate than from digital slides.

What happens when dealing with other microfossils that cannot be isolated and/or have complex shapes? Palynomorphs (pollen, spores, dinoflagellate cysts, acritarchs, etc.) fall into this category. They are usually mounted on microscopic slides, often alongside various detrital material. Initial attempts to create automated pollen recognition systems focused on the texture of the surface of the pollen wall (e.g., Langford, et al., 1990) as involving the capture of high-resolution images using scanning electron microscopy. While this method achieved a high level of accuracy (around 94.3%), it posed limitations in terms of investment and broader applications.

Subsequent developments for automated recognition systems involved the use of automated stages on microscopes (capable of moving in three dimensions), image acquisition (pollen reference slides of modern and fossil taxa) and classification or convolutional neural network (e.g., France et al. 2000; Stefanowicz et al., 2023). Creating a training set for such systems can be laborious but is typically a one-time effort. However, several challenges have emerged, including variations in the orientation of the palynomorphs within the mounting sealant, not all pollen are at the same depth on the slide, the presence of broken specimens, other materials that could be mistaken for palynomorph, and the presence of new species or genus.

Is the investment in terms of time and funding worth the effort? The significant number of publications in the last decade seems to support this approach (e.g., (Amao, 2021; Rostami et al., 2023; Ferreira-Chacua and Koeshidayatullah, 2023; Wang et al., 2023; Zhang et al., 2020; Itaki et al., 2020; Mimura and Nakamura 2023) (around 50 articles were identified using the following key-words: “automated identification” and “pollen” on the Web of Science).

Despite the advancements in computational power and algorithms over the years for capturing discriminating characteristics of microfossils, a consistent challenge highlighted in the academic literature is the quality of training datasets and the considerable number of images required to attain high accuracy, leading to a storage issue.

**4. Accuracy versus efficiency?**

Microfossil assemblages, regardless of their type, collectively provide a wealth of information that allows us to gain insight into past environmental conditions and the processes that led to the deposition and preservation of these microfossils. However, we should not disregard materials found in samples, as they can provide additional indications of specific conditions that might not be evident by microfossils assemblages alone.

Broken specimens, if they are genuine and not artificially created during laboratory processing, can tell us a story of poor preservation, possibly high-energy depositional environments. Morphotypes can be used as valuable indicators of unstable or transitional environmental conditions. Furthermore, occasionally, entirely new species or even genera may appear and if they are absent from the training set of an automated system, they risk being overlooked entirely. Micropalaeontologists perfect their skills through years of practice and study which can help to discern nuances for accurate interpretation of microfossil assemblages or as close as it can be. On the other hand, identification can be prone to subjectivity which decreases the accuracy.

The evidence that AI systems are more accurate and consistent has been well documented, as they usually excel in pattern recognition. Furthermore, they can handle large datasets in a small amount of time in a rigorous manner, therefore demonstrating their superior capabilities compared to human ones.

We can therefore envision a future in which a constructive synergy between AI systems and micropalaeontologists would accelerate the research process and enable the handling of larger datasets in less time.

**5. From species identification to assemblage interpretation**

Interpretating microfossil assemblages is a rather complex task for the specialist, relying on knowledge accumulated over many years and an ability to synthesis data and to integrate them in a framework beyond the discipline of micropalaeontology. One must consider the geological and ecological context, depositional processes and taphonomic issues to cite a few. This knowledge is built upon integrating academic sources, own research and usually working within a scientific community. The access of online resources (from databases to open-access papers) has exponentially multiplicated our ability to further our skills to improve the interpretation of fossil assemblages.

Therefore, it is logical to apply this same methodological approach when using GAI (Generated Artificial Intelligence) as they have the capability to instantly access online to a plethora of scientific data. GAI are constrained in boundaries that are implemented by the developers and users, as well as some sense of ethical values. Consequently, it is possible to envision a scenario where the specialist or the non-specialist uses GAI to help them to analyse the significance of microfossil assemblages.

CNNs can help to identify patterns in assemblages, both in terms of spatial and temporal distributions, as well as detecting anomalies. GAI algorithms can be trained to use species indicators for the reconstruction of specific environmental conditions. Time-series analysis is already extensively utilised to discern trends and cycles in geological records. GAIs have the capacity to synthesis multiproxy records to produce a comprehensive interpretation. Machine learning techniques, data mining, clustering are tools routinely used by the micropalaeontologists with various dedicated softwares; GAI can implement all these techniques in a single command.

Therefore, what is stopping us from fully embracing the use of AIs to carry on the work of micropalaeontologists?

Although GAI's capacity to access scientific information is almost limitless, it has not yet acquired the nuanced expertise that specialists have built over years of study. GAI can only produce identifications and interpretations within a set of predefined parameters, and therefore, it may overlook information not included in its training datasets, which specialists have access to.

Discussions with colleagues in my discipline on this topic, particularly regarding the use of automated pattern recognition, often end with a defeated sigh. Either they are worried that they could be easily replaced, with the consequence for this discipline of losing lifelong expertise, or they have tried to develop this technique and quickly realized the limitations of the system. The creation of training datasets for AI systems is a time-consuming task that necessitates specialists to identify and annotate specimens. With a declining number of experts in recent decades, it has become increasingly challenging to find the human resources required to develop high-quality AIs covering different disciplines in micropalaeontology, especially for analysing fossil records covering millions of years of Earth history. Given the current funding landscape, one might question who would be interested in subsidising this line of research, especially when oil exploration companies typically rely on seismic surveys for correlating geological formations and academia is gradually disengaging from basic science.

**6. Conclusions**

This perspective was initially started with the vision that GAI may not be the panacea for easily replacing years of expertise. While the author was compiling academic evidence on the use of machine learning systems, neural network techniques and AI systems on identifying microfossils, they were surprised by the large number of studies demonstrating the high accuracy of automated systems in identifying a number of microfossil taxa. Some studies have highlighted that there is further need for development before pattern recognitions can reach 100% accuracy for all types, in particular for morphologically challenging specimens. However, it seems that their ability for correct identification is usually better than that of specialists due to the lack of subjectivity and human errors.

However, there is still a way to go before we can satisfactorily rely on using GAI to provide us with a reliable interpretation of microfossil records despite their almost unlimited access to academic resources. Micropalaeontologists bring a deep understanding of the discipline, including domain-specific knowledge and contextual insights that are challenging for GAI to replicate fully. Therefore, a collaborative approach, where GAI augments human expertise, is likely to be the most effective way to interpret microfossil assemblages accurately.

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**Declaration of generative AI and AI-assisted technologies in the writing process**

During the preparation of this work the author used ChatGPT in order to correct the English. After using this tool/service, the author reviewed and edited the content as needed and take full responsibility for the content of the publication.

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