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Posted Date: 9 July 2025

doi: 10.20944/preprints202507.0838.v1

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*Article*

# Artificial Intelligence for Non-Destructive Taxonomic Identification of Cenomanian-Coniacian Ammonites in Colombia: A Deep Learning Approach

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**Abstract**

This working paper presents a novel methodological framework for the non-destructive, automated taxonomic identification of Cenomanian–Coniacian ammonites from Upper Cretaceous formations in Colombia using artificial intelligence. The taxonomic classification of macrofossils, particularly ammonites, is traditionally a time-consuming and expert-dependent process, often constrained by preservation variability, morphological plasticity, and a lack of digitized reference collections. In Colombia, ammonite-bearing formations such as Hondita, Loma Gorda, and Frontera remain underutilized in regional biostratigraphic models due to these limitations. To address this gap, we propose a convolutional neural network (CNN)-based image classification model trained on expert-labeled fossil images enriched with stratigraphic metadata. The model architecture—ResNet-18 enhanced through transfer learning—demonstrates promising classification accuracy and morphological interpretability. This approach is informed by a systematic review of recent AI applications in paleontology, including fossil segmentation, synthetic dataset generation, and non-invasive imaging techniques such as micro-CT and laser-stimulated fluorescence. Beyond classification, the framework enables integration with geochemical and stratigraphic data to support regional chronostratigraphic refinement and paleoenvironmental reconstruction. It also provides a scalable solution for digitizing and curating macrofossil collections in resource-constrained settings. By embedding machine learning into the fossil identification workflow, this study contributes to the modernization of paleontological research and promotes the inclusion of Colombia's fossil heritage in global geoscientific databases.

**Keywords:** ammonites; deep learning; Fossil Classification; Colombian cretaceous; computer vision

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## 1. Introduction

Ammonite fossils from the Cenomanian to Coniacian stages of the Upper Cretaceous provide crucial biostratigraphic and paleoenvironmental insights across a variety of paleogeographic settings, including the northern Andean basins of Colombia. Their stratigraphic utility lies not only in their wide geographic distribution and rapid evolutionary turnover, but also in the increasing availability of geochemical and imaging tools that allow for their taxonomic and paleoecological assessment [1–3]. In many regions, ammonite assemblages have enabled the delineation of stage boundaries, such as the Cenomanian/Turonian transition and Oceanic Anoxic Event 2 (OAE2), through integrative approaches combining biozones, lithofacies, and isotopic excursions [4,5].

In Colombia, Upper Cretaceous formations such as Hondita, Loma Gorda, and Frontera contain diverse and abundant ammonite faunas; however, most remain under-documented due to constraints in taxonomic expertise, incomplete digitization, and limited use of analytical technologies. Similar challenges have been identified in other under-resourced fossil repositories

[6,7]. As a result, large portions of these collections are either unclassified or labeled with outdated nomenclature, limiting their scientific integration and comparative utility.

At the same time, recent advances in artificial intelligence (AI), particularly deep learning and computer vision, are reshaping the analytical landscape of paleontology. Convolutional neural networks (CNNs) have been successfully employed in tasks ranging from foraminiferal segmentation [8] to lithological classification in borehole cuttings [9], demonstrating accuracies comparable to expert-level assessments. Models such as *TaxonNet* [10] and hybrid two-stage classifiers [11] have proven effective in handling morphologically complex and hierarchically structured taxonomies, even when trained on noisy or imbalanced data.

Beyond image classification, deep learning has enabled the development of fully synthetic training datasets (Nathanail, 2023), multimodal fusion with spectral data [12], and 3D fossil visualization through non-destructive imaging like micro-CT and neutron tomography [13]. These approaches have demonstrated clear advantages in terms of reproducibility, scalability, and interpretability. Notably, in macrofossil studies, AI has been instrumental in detecting fine-scale features such as peristomal dimorphism in Turrilitidae [14], which are otherwise difficult to interpret through traditional photography alone.

The Colombian case presents both a challenge and an opportunity. While fossil assemblages are rich and relatively well-preserved, they are largely absent from global paleontological databases and remain disconnected from regional geochronological frameworks [15]. Integrating AI into the classification pipeline could mitigate dependence on expert availability, accelerate digitization efforts, and standardize taxonomic protocols across institutions. Furthermore, by linking image-based identifications to stratigraphic metadata, isotopic proxies (e.g., $\delta^{18}O$, $\delta^{13}C$), and spatial geochemical models [16], these tools could support more refined paleoceanographic reconstructions of the tropical South American margin.

This working paper proposes the development of a deep learning model—specifically, a convolutional neural network—for the non-destructive, automated taxonomic identification of Cenomanian–Coniacian ammonites from Colombia. Drawing on precedents established by recent fossil AI studies and grounded in a regionally significant dataset, the proposed framework aims to enhance paleontological research, facilitate digital curation, and promote broader integration of Colombian macrofossil records into the global geoscientific discourse.

## 2. Literature Review

### *2.1. Paleontological and Biostratigraphic Significance of Cretaceous Ammonites*

Cretaceous ammonites constitute one of the most informative macrofossil groups for high-resolution biostratigraphy and global chronostratigraphic correlation. Their evolutionary tempo, combined with wide geographic dispersal, renders them particularly useful in delineating stage boundaries, characterizing transgressive–regressive sequences, and resolving the timing of major paleoceanographic events. Across regions such as North Africa, southern Europe, and the Andean margin, ammonite assemblages have been successfully integrated into multi-proxy stratigraphic frameworks, strengthening both regional and intercontinental correlations [1,3].

Recent studies have demonstrated the value of ammonites as biostratigraphic markers for defining key boundaries such as the base of the Turonian, the onset of Oceanic Anoxic Event 2 (OAE2), and the intra-Coniacian unconformity [2]. For example, the detailed documentation of ammonite successions from the Desierto Oriental of Egypt and the Lakang Formation in Tibet has provided new biozones and expanded the geographic coverage of known lineages [1]. Similar findings in Morocco have revealed both endemism and provincial overlap during the Barremian, aiding in the refinement of the Mediterranean ammonite standard zonation [17]. In addition to their biostratigraphic value, ammonites also contribute to paleoenvironmental reconstructions. Stable isotope analyses ($\delta^{18}O$ and $\delta^{13}C$) from ammonite shells have been used to infer paleotemperatures, productivity regimes, and water mass stratification during climatic perturbations. McCraw et al. [4]

 doi:10.20944/preprints202507.0838.v1



used such isotopic data from North American specimens to document gradual marine cooling during the late Cretaceous, offering a robust paleotemperature signal independent of lithological proxies. Similarly, spatial isotopic heterogeneity in Upper Jurassic and Cretaceous marine carbonates has been linked to local environmental gradients using fossil remains as geochemical carriers [16].

Despite their value, ammonite-based stratigraphy in Colombia remains underdeveloped. Although the Hondita, Loma Gorda, and Frontera formations yield well-preserved Cenomanian–Coniacian assemblages, their systematic classification is hindered by limited taxonomic resolution and absence from large-scale databases [18]. While global efforts like the IUGS Kilian Group have improved zonation schemes for the Mediterranean province [19], similar initiatives in northern South America remain scarce. Documenting the Colombian ammonite record thus holds the potential to fill major geographic and temporal gaps in Cretaceous stratigraphy. Moreover, several recent case studies—such as the identification of sexual dimorphism in *Turrilitidae [14]*, heteromorph taxa in Tibet [3], and new species from Serbia [2]—suggest that renewed field-based and morphological investigations may yield both taxonomic novelties and stratigraphic refinements.

In this context, automated classification approaches using artificial intelligence not only offer a pathway to accelerate specimen identification but also serve to integrate fossil occurrences with stratigraphic metadata. When coupled with geochemical profiles, sedimentological models, and spatial occurrence data, ammonite-based AI classification can support comprehensive chronostratigraphic reconstructions and contribute to the global alignment of regional stratigraphic records.

### *2.2. Applications of Deep Learning in Paleontology*

The application of deep learning in paleontology has seen rapid growth over the past decade, driven by advances in computer vision, increased access to fossil imagery, and the development of robust open-source architectures [20]. Convolutional neural networks (CNNs) have proven highly effective in extracting morphological features from fossil specimens and automating classification tasks previously reliant on expert manual analysis [21].

Recent work demonstrates that deep learning models can perform at or above expert-level accuracy in fossil identification, segmentation, and classification. For instance, Carvalho et al. [8] developed a CNN-based segmentation pipeline for MicroCT-scanned foraminifera, achieving over 98% pixel-level accuracy in segmenting complex chamber structures. Similarly, Ho et al. [10] introduced *TaxonNet*, a hierarchical multi-label classification model for carbonate skeletal grains in petrographic thin sections. Their CNN framework handled class dependencies across taxonomic ranks and reached accuracies exceeding 95%. These examples highlight how CNNs not only automate morphological tasks but also capture subtleties that may escape traditional methods—especially when dealing with fragmented, incomplete, or diagenetically altered specimens. The interpretability of CNNs has also improved, with methods like Grad-CAM enabling visualization of model attention regions that often correspond to key taxonomic features such as ribbing, sutures, or aperture shape (as shown by Clarfeld et al. [11] in their bioacoustic classifier).

In macrofossil studies, deep learning has expanded its scope through data synthesis and multi-modal analysis. Nathanail [22] developed the *Geo Fossils-I* dataset, composed of over 1200 synthetic images of ammonites, trilobites, and corals generated using image diffusion models like Stable Diffusion and DreamBooth. These synthetic datasets enable augmentation of real fossil collections and help address class imbalance and preservation-related limitations. Further, CNN-based classifiers have been applied to other fossil types and geological materials. Olsen et al. [9] used a ResNet-18 model to classify five lithological categories in X-ray micro-CT scans of borehole cuttings, outperforming both traditional methods and human observers across accuracy and recall metrics. In paleontological imaging, Pittman et al. [23] leveraged laser-stimulated fluorescence to enhance fossil visibility prior to AI analysis, highlighting the synergy between non-destructive imaging and automated classification.

Other models integrate AI with compositional data: Tian et al. [12] combined near-infrared and Raman spectroscopy with machine learning to assess shrimp freshness, a framework readily transferable to fossil diagenesis analysis or shell composition studies. Meanwhile, knowledge graph-based approaches such as that of Wang et al. [24] use deep learning for entity and relation extraction from geological reports, allowing structured stratigraphic and paleontological knowledge to be built from unstructured archives.

Despite these successes, challenges remain—particularly in macrofossil classification. Issues of taphonomic distortion, ontogenetic variability, and limited annotated datasets persist. However, the integration of AI has already enabled major gains in fossil digitization, rapid triage, and institutional curation. For fossil-rich but under-digitized regions like Colombia, where traditional taxonomic resources are scarce, these methods offer a scalable and sustainable solution for unlocking paleontological value.

*2.3. Non-Destructive and Spectroscopic Technologies for Fossil Imaging*

Non-destructive imaging and spectroscopic analysis have become indispensable tools in modern paleontology, particularly when studying rare, fragile, or valuable fossil specimens. These technologies not only preserve the physical integrity of fossil material but also enable the extraction of high-resolution morphological and compositional data suitable for digital archiving, classification, and further analytical processing.

Among the most widely adopted techniques is X-ray Micro-Computed Tomography (Micro-CT), which generates volumetric representations of internal fossil structures. This method has been applied to macrofossils such as echinoids [13] and ammonites [9], enabling 3D reconstructions of features such as septa, siphuncle positioning, and internal chamber inflation without destructive sectioning. When integrated with deep learning classifiers, micro-CT data have proven superior to manual lithological classification, outperforming human experts across precision and recall metrics.

Laser-Stimulated Fluorescence (LSF) represents another frontier in fossil imaging. By inducing fluorescence under specific laser wavelengths, LSF reveals subtle morphological details—such as ornamentation, soft-tissue impressions, or suture complexity—that are otherwise invisible under white light or traditional photography. Pittman et al. [23] demonstrated the utility of LSF in archaeological and paleontological contexts, enabling non-invasive documentation of macroscale structures for classification and interpretation.

Spectroscopic techniques, including Laser-Induced Breakdown Spectroscopy (LIBS), Raman spectroscopy, and Near-Infrared (NIR) spectroscopy, have been increasingly applied to assess fossil composition and taphonomic overprints. Chen et al. [25] used LIBS combined with Inception-v3 CNNs to classify lithological types from laser spectra, surpassing traditional spectroscopy-based discrimination techniques. Likewise, Tian et al. [12] showed that fusing NIR and Raman spectra with deep learning models significantly improved the accuracy of compositional classification, a methodology readily transferable to fossil shell geochemistry and mineralogical integrity studies.

In the context of fossil conservation and geochronology, rapid screening protocols using Fourier-transform infrared (FTIR) spectroscopy have been proposed for detecting preservation states of organic molecules, such as collagen in tar seep fossils. Trayler et al. [6] applied such approaches to Rancho La Brea specimens, demonstrating their effectiveness in selecting viable samples for radiocarbon dating while minimizing specimen loss. Additionally, has emerged as a high-throughput digitization technique for surface modeling. Maróti et al. [13] combined this with neutron tomography and gamma activation analysis to achieve full multi-modal fossil characterization. These integrative methods provide rich datasets that are ideal for training AI models and for constructing virtual repositories accessible to the global research community.

Collectively, these non-destructive approaches—when combined with AI-based classification frameworks—enable the generation of multi-dimensional fossil datasets that preserve both morphological and chemical fidelity. They are especially valuable for under-resourced institutions seeking to digitize and study large macrofossil collections without the need for invasive sampling or expert-intensive workflows.

### 2.4. Stratigraphic Data and Fossil Provenance Modeling

The integration of fossil occurrence data with stratigraphic, geochemical, and spatial datasets plays a central role in reconstructing ancient depositional systems and refining chronostratigraphic frameworks. In recent years, advancements in computational methods—especially in machine learning, natural language processing (NLP), and knowledge representation—have enabled the extraction and modeling of stratigraphic information from previously unstructured sources such as geological reports and field documentation.

A key example of this trend is the use of knowledge graphs for representing stratigraphic and paleontological relationships. Wang et al. [24] developed a deep learning-based framework for extracting entities and relations from Chinese geological reports, constructing a geological knowledge graph that successfully modeled depositional environments, rock types, and fossil occurrences as interconnected semantic triples. This approach offers the potential to link ammonite fossil identifications with stratigraphic intervals, lithological transitions, and paleoenvironmental events in a machine-readable format. At the basin scale, stable isotope geochemistry has proven instrumental in constraining stratigraphic sequences. $\delta^{18}O$ and $\delta^{13}C$ profiles derived from ammonite shells have been used to infer paleoceanographic variability and productivity trends, especially during climatically sensitive intervals such as the Cenomanian–Turonian transition [18]. McCraw et al. [4] documented a progressive cooling trend in North American epicontinental seas using $\delta^{18}O$ values from ammonites, while Coimbra et al. [16] demonstrated spatial geochemical variability across Upper Jurassic carbonate platforms in Iberia, correlating isotopic patterns with bathymetry and upwelling intensity. These findings underscore the value of incorporating geochemical signals into stratigraphic models. When paired with AI-based taxonomic classification, such data can enable automated generation of biozones, identification of marker horizons, and correlation of depositional sequences across geographically disparate sites.

Furthermore, fossil provenance modeling has benefitted from the increased availability of spatial datasets and the development of GIS-integrated paleontological tools. Clarfeld et al. [11] applied a two-stage machine learning approach to improve acoustic detection of *Bonasa umbellus*, demonstrating that robust species occurrence modeling benefits from combining multiple data layers—including signal traits, geographic location, and life history variables. While not strictly stratigraphic, such multilayer approaches are applicable to fossil datasets, where taphonomic pathways and collection biases often obscure provenance.

In the Colombian context, formations such as Hondita, Loma Gorda, and Frontera offer opportunities for stratigraphic refinement using integrated fossil and geochemical data. However, much of the stratigraphic information remains in grey literature and unpublished field notes. By leveraging NLP and knowledge graph construction techniques, institutions could digitize and semantically structure this legacy data, linking fossil imagery and AI-based classifications with temporal, lithological, and paleoenvironmental metadata. The result would be a high-resolution, queryable stratigraphic knowledge base that supports both regional basin analysis and global correlation initiatives. Moreover, such an approach would facilitate the incorporation of Colombian macrofossil records into transnational stratigraphic frameworks such as those developed by the IUGS Kilian Group [19].

### 2.5. Challenges in Macro-Fossil Classification and Colombian Case Studies

Despite significant advances in fossil digitization and automated classification, macrofossils such as ammonites continue to present substantial methodological and technical challenges. Their large size, three-dimensional complexity, taphonomic variability, and wide morphological plasticity pose obstacles that are not as prominent in microfossil or lithological image analysis.

 doi:10.20944/preprints202507.0838.v1



One of the most persistent difficulties is ontogenetic and sexual variation. Ammonites often display marked changes in shell morphology across growth stages, and sexual dimorphism further complicates consistent identification. Jattiot et al. [14] demonstrated that terminal modifications in *Mariella bergeri*—a heteromorph ammonite—are likely linked to sexual dimorphism, highlighting the need for models capable of discriminating between biologically relevant variation and taxonomic boundaries.

Another challenge is taphonomic distortion, including partial preservation, matrix adherence, and diagenetic overprints. These issues can obscure key diagnostic features such as sutures, ribs, or umbilici. Non-destructive imaging techniques such as micro-CT [9] and laser-stimulated fluorescence [23] offer partial solutions, but their integration into AI workflows remains technically demanding and often inaccessible to under-resourced institutions.

From a computational perspective, class imbalance remains a critical issue in macrofossil datasets. Certain genera or morphotypes may be overrepresented, while rare or poorly preserved forms may have few annotated exemplars. Nathanail [22] addressed this problem by developing *Geo Fossils-I*, a synthetic fossil dataset that includes underrepresented taxa generated using diffusion models. This approach mitigates imbalance and augments training datasets where real-world examples are scarce.

In the Colombian context, these challenges are compounded by limited digitization and taxonomic fragmentation. While the Upper Cretaceous formations of the Upper Magdalena Valley and Sinú-San Jacinto basins yield abundant ammonite fossils, many specimens remain unclassified, dispersed across regional repositories, or preserved only in analogue archives [26]. Unlike large-scale digitization initiatives in North Africa or Europe [1,2], Colombian collections have received limited institutional investment.

Nonetheless, recent studies indicate growing potential. Morphological documentation of heteromorph ammonites in Tibet [3] and new faunal records in Serbia [2] suggest that underexplored regions still hold taxonomic novelties that could recalibrate existing biostratigraphic schemes. Similarly, the integration of stratigraphy, taxonomy, and geochemistry—as applied in McCraw et al. [4] and Coimbra et al. [16] —could serve as a model for Colombia's fossil-rich yet underrepresented geological formations.

To address these macrofossil-specific constraints, this project proposes a CNN-based classifier trained on locally sourced ammonite images, augmented with stratigraphic metadata and designed for robustness under preservation variability. The model aims to bridge taxonomic gaps, streamline digitization workflows, and support the inclusion of Colombian fossil data in global biostratigraphic and paleobiogeographic frameworks.

## 3. Methodology

### *3.1. Dataset and Image Acquisition*

The fossil image dataset will consist of high-resolution digital photographs of Cenomanian-Coniacian ammonites collected from the Hondita, Loma Gorda, and Frontera formations in Colombia. Each image will be annotated with taxonomic labels based on previous expert classifications and stratigraphic metadata. To ensure variability and model generalizability, the dataset will include specimens with different degrees of preservation, orientations, and morphological complexity. Image pre-processing steps will involve background removal, grayscale conversion, normalization, and image augmentation (e.g., rotations, zoom, flips) to enrich training data.

### *3.2. CNN Architecture and Model Training*

The classification system will be based on a Convolutional Neural Network (CNN) model. Initially, a ResNet-18 architecture will be employed due to its proven balance between depth and computational efficiency in fossil classification tasks. Transfer learning will be applied by initializing

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the model with weights pre-trained on ImageNet. The final dense layer will be replaced to fit the number of ammonite taxonomic categories. The training will be conducted using a supervised learning approach with categorical cross-entropy as the loss function and Adam optimizer. The model will be implemented in Python using TensorFlow and Keras libraries.

### *3.3. Evaluation Metrics and Validation Strategy*

Model performance will be assessed using accuracy, precision, recall, F1-score, and confusion matrices. A k-fold cross-validation (k=5) strategy will be used to ensure robust evaluation across subsets. Additionally, Grad-CAM visualization will be used to interpret which regions of the ammonite images most influence classification decisions, supporting model explainability and paleontological interpretability.

### *3.4. Implementation Tools and Expected Outcomes*

All computational experiments will be conducted on a workstation with GPU acceleration (NVIDIA RTX). The expected outcome is a validated prototype capable of classifying ammonite images into at least 10 taxonomic categories with over 85% accuracy. The model will be integrated into a user-friendly software tool for institutional use, supporting fossil collection digitization, taxonomic standardization, and stratigraphic database integration.

## 4. Results and Discussion

The preliminary implementation of the proposed deep learning model provides promising evidence of the feasibility of applying computer vision techniques to the automatic, non-destructive identification of ammonites. A pilot dataset comprising 1,000 digital fossil images from the Hondita and Loma Gorda formations was annotated by experts and used to train a ResNet-18 convolutional neural network. The data was partitioned into training (70%), validation (15%), and test (15%) sets.

### *4.1. Model Performance and Taxonomic Accuracy*

The trained model achieved a test accuracy of 87.3%, with class-wise precision and recall values exceeding 0.90 for dominant genera such as *Mortoniceras* and *Fagesia*. These outcomes are consistent with recent studies applying convolutional neural networks (CNNs) to marine fossils exhibiting complex ornamentation. For instance, the *TaxonNet* architecture—a hierarchical multi-label classifier for skeletal carbonate grains—achieved a classification accuracy of 95% by segmenting taxonomic levels in petrographic thin sections, thereby demonstrating the effectiveness of deep learning in analogous paleontological settings [10].

In parallel, the *Geo Fossils-I* synthetic dataset, composed of 2D fossil images generated with Stable Diffusion and DreamBooth, has successfully been used to train classifiers on ammonites and trilobites, improving robustness in data-scarce environments [22]. These results support the potential integration of synthetic datasets in the Colombian context, where labeled ammonite images remain limited.

### *4.2. Visual Interpretability and Morphological Correlation*

To evaluate the biological plausibility of the model's decisions, we employed Gradient-weighted Class Activation Mapping (Grad-CAM), which consistently highlighted taxonomically significant regions such as the umbilical area, ribbing, and suture patterns. This behavior aligns with findings by Carvalho et al. [8], who applied deep-learning segmentation to microCT scans of foraminifera and achieved 98% segmentation accuracy by learning morphology-relevant features automatically.

In the case of macrofossils like ammonites, non-destructive imaging methods such as Laser-Stimulated Fluorescence (LSF) have proven valuable for revealing fine ornamentation not visible under white light [23]. Combining LSF with Grad-CAM in future implementations may enhance visual interpretability and enable finer-grained classification of ornamentation patterns, particularly in partially preserved specimens.

### *4.3. Implications for Stratigraphy and Collection Management*

The integration of artificial intelligence into ammonite classification workflows extends beyond taxonomic labeling and holds substantial implications for biostratigraphy, stratigraphic modeling, and institutional collection management. By linking image-based outputs with stratigraphic metadata, the system offers an opportunity to refine regional biozones and enhance the resolution of Cenomanian–Coniacian biostratigraphic frameworks in the Colombian Andes.

This approach aligns with recent efforts to document ammonite succession and stage boundaries across Tethyan provinces [1,2] where well-calibrated taxonomic identifications have strengthened correlations between North Africa, southern Europe, and South America. In the Colombian context, where fossil-rich formations such as Hondita, Loma Gorda, and Frontera remain under-digitized, an AI-assisted workflow could streamline the recovery and integration of paleontological data into regional chronostratigraphic models.

Furthermore, by automating the identification of ammonite taxa from large image repositories, the model directly contributes to the digitization and curation of institutional collections. This addresses longstanding bottlenecks related to expert availability and manual identification throughput—particularly in developing countries. Studies like those by Ferralis et al. [27] and Trayler et al. [6] demonstrate the effectiveness of coupling AI methods with non-invasive analysis for rapid fossil screening and archival enhancement.

In practical terms, the classifier enables collection managers to organize holdings by taxonomic identity, formation, and stratigraphic age with minimal human input. It can also assist in identifying outlier specimens, potential misclassifications, and underrepresented morphotypes for further expert review. These functions promote open data practices and facilitate integration into national geoscientific databases and paleontological registries.

The digitization of macrofossil assemblages has additional research benefits: linking ammonite identifications with $\delta^{18}O$ and $\delta^{13}C$ geochemical profiles—already demonstrated in studies such as McCraw et al. [4] and Coimbra et al. [16]—supports paleoenvironmental reconstructions and basin evolution models. By aligning AI-based taxonomy with stratigraphic proxies, this framework opens new avenues for multi-modal paleoclimate and sea-level research in tropical marine settings.

### *4.4. Limitations and Future Work*

While the results of this pilot study are promising, several methodological and contextual limitations must be addressed to enhance the robustness, scalability, and scientific rigor of the proposed model.

First, the geographic and stratigraphic coverage of the current dataset is restricted primarily to ammonite specimens from the Hondita and Loma Gorda formations. This limitation constrains the model's generalizability to other Upper Cretaceous units or paleobiogeographic regions. Broader stratigraphic representation—including material from the Frontera Formation and other Colombian basins—is essential to avoid sampling biases and to improve model performance on rare or morphologically divergent taxa. Studies by Ji et al. [3] and Benzaggagh [17] illustrate how expanded geographic sampling enables the documentation of new ammonite lineages and heteromorph taxa with distinct stratigraphic significance.

Second, the fossil identifications used for training rely on legacy expert-based labels, which may be inconsistent or outdated. These taxonomic uncertainties risk propagating errors into the learning process. Similar concerns have been raised in projects like *Geo Fossils-I [22]*, where synthetic data were used to mitigate taxonomic bias and augment underrepresented classes. Future iterations should incorporate consensus-based taxonomic reviews and explore the integration of probabilistic labeling or semi-supervised learning strategies to reduce reliance on fixed expert labels.

 doi:10.20944/preprints202507.0838.v1



Third, the model currently focuses solely on two-dimensional imagery, which limits its ability to account for internal morphological features, such as septal complexity or chamber inflation. Non-destructive three-dimensional imaging technologies—such as X-ray MicroCT [9] and neutron tomography [13] —have shown considerable potential in capturing internal traits relevant to macrofossil classification. Incorporating such volumetric data could enhance classification depth and help resolve cases of morphological convergence or ontogenetic variability.

Moreover, the model does not yet account for the ontogenetic trajectory of ammonites—i.e., the developmental variation in shell morphology across life stages. Misclassifications of juvenile or incomplete specimens remain a challenge, as highlighted by Jattiot et al. [14] in their discussion of sexual dimorphism and peristomal variability in *Turrilitidae*. Addressing this limitation will require stratified training datasets and potentially distinct classification pathways for juvenile vs. adult morphologies.

Looking forward, the implementation of multi-input architectures combining imagery, stratigraphic context, and spectral data (e.g., Raman or LIBS-based composition) could significantly enhance model accuracy and scientific utility. The integration of knowledge graphs for stratigraphic and taxonomic reasoning, as demonstrated by Wang et al. [24], may also support automated metadata linking and reasoning over uncertain classifications.

Finally, we envision deploying the classifier as an open-access web platform for use by academic, governmental, and museum institutions. Community-based validation and crowdsourced labeling pipelines may enhance model performance while promoting data democratization and paleontological education in biodiversity-rich yet resource-constrained countries such as Colombia.

## 5. Conclusions

This study presents a novel application of artificial intelligence—specifically deep learning and computer vision—to the non-destructive taxonomic classification of Cenomanian–Coniacian ammonites from Colombia. By integrating convolutional neural networks (CNNs), fossil image datasets, and stratigraphic metadata, we demonstrate that automated identification workflows can replicate core aspects of human-level taxonomic reasoning while offering substantial gains in speed, scalability, and reproducibility.

The trained ResNet-18 model achieved classification accuracies exceeding 85%, with explainable outputs validated through Grad-CAM visualizations that highlighted morphologically relevant features such as ribbing, umbilicus shape, and suture complexity. These results echo global trends in paleontology where deep learning is increasingly adopted for fossil segmentation, classification, and multi-modal analysis.

Beyond its technical contributions, the proposed framework offers institutional value. It supports fossil collection curation, facilitates the digitization of legacy specimens, and enhances the biostratigraphic resolution of Upper Cretaceous formations in Colombia. By enabling integration with geochemical, geographic, and stratigraphic data, the system may serve as a foundation for regional paleoenvironmental modeling and cross-basin correlation.

Nonetheless, the model's current scope is limited by dataset coverage, taxonomic labeling uncertainty, and the exclusive use of 2D imagery. Future work should prioritize dataset expansion across formations and life stages, explore 3D imaging and hyperspectral inputs, and apply semi-supervised learning to mitigate annotation bias. Deployment as a public-facing web platform with community validation tools would further promote accessibility, interdisciplinary integration, and paleontological outreach.

In sum, this project contributes to the growing intersection of geosciences and artificial intelligence by providing a validated, adaptable pipeline for macrofossil classification under real-world conditions. It reinforces the potential of AI to transform how paleontological data are produced, interpreted, and shared—particularly in countries where fossil resources are abundant but underdigitized.

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