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RESEARCH ARTICLE

Supervised Seismic Facies Classification in Ataga Field of Niger Delta Basin using a Thalweg Tracker and Deep Learning Approach

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Abstract

Seismic facies classification remains a critical yet challenging task in subsurface characterization due to the complexity of depositional systems and limitations of manual interpretation. This study presents a supervised deep learning workflow for seismic facies prediction using a dip-steered median filtered (DSMF) seismic volume. Ten facies label sets, representing minima and maxima responses, were derived from unsupervised vector quantization (UVQ) clustering and subsequently refined using Thalweg tracking, with 1,500 samples per class. These labels, together with the DSMF volume, were used to extract 3D cubelets (41×41×3) for training convolutional neural networks (CNNs). Three architectures, LeNet, ResNet18, and SimpleNet, were implemented and evaluated based on classification performance and geological consistency of predicted facies volumes. Among the tested models, LeNet demonstrated superior performance, producing laterally continuous and stratigraphically consistent facies distributions that closely follow the geometry of seismic reflectors. The predicted facies exhibit clear differentiation between sand-prone, shale-dominated, and heterolithic units. Validation using gamma-ray (GR) and density (RHOB) logs confirms a strong correspondence between predicted facies and lithological variations, with sand intervals corresponding to low GR responses and shale intervals to high GR values. Minor limitations include partial merging of polarity-based facies classes; however, overall depositional patterns remain well preserved. The results highlight the effectiveness of a DSMF-driven LeNet approach for reliable and geologically meaningful seismic facies classification.

Keywords: reservoir characterization, deep learning, Niger Delta basin, Ataga field, seismic facies classification, thalweg tracker, convolutional neural network.

1 Introduction

Seismic reflections from acoustic boundaries signify stratigraphic boundaries in the subsurface, reflecting the architecture and geometry of the subsurface

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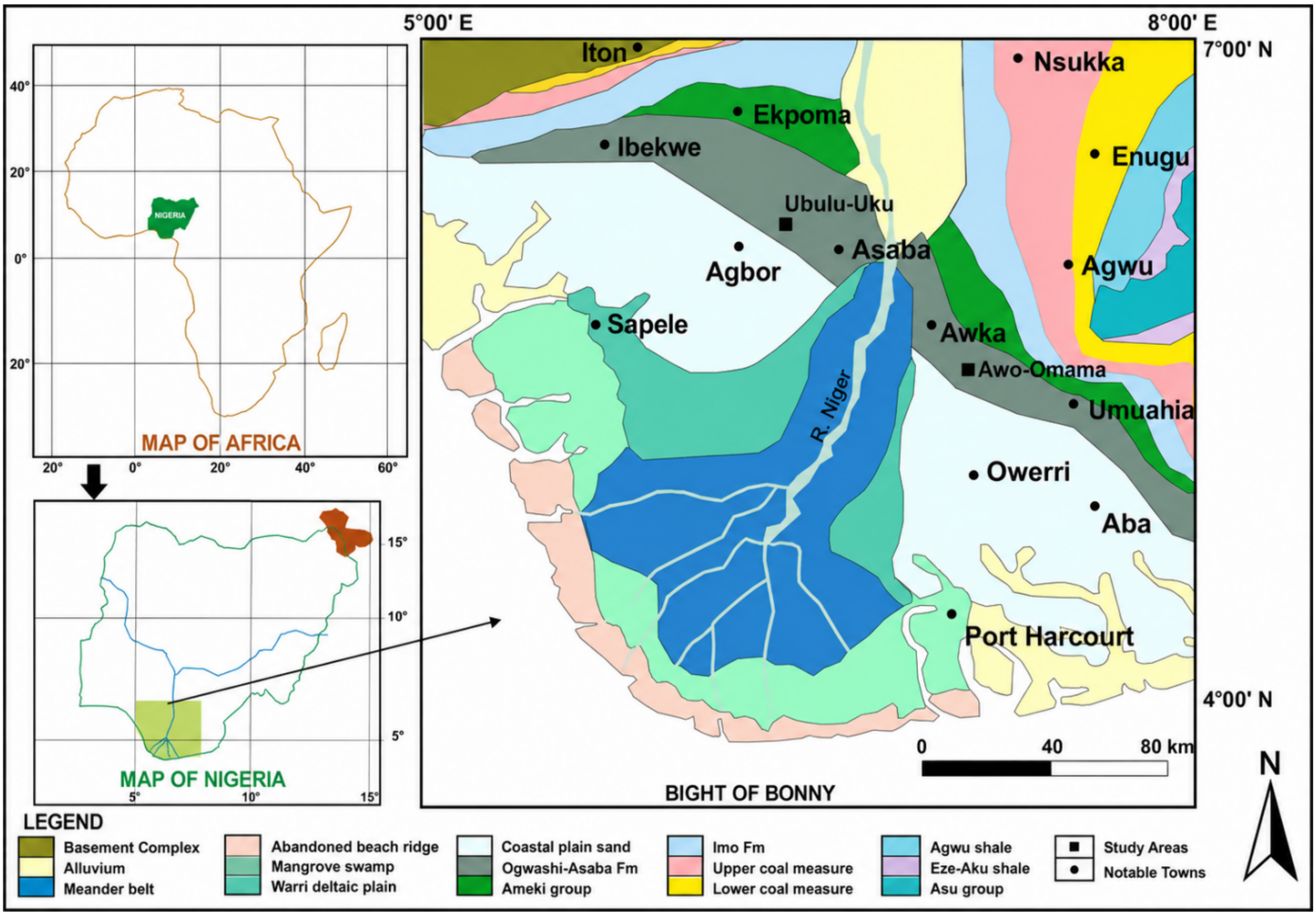

Figure 1. Geological map of Nigeria showing the Niger Delta Basin [40].

stratigraphy, and the shaping processes [1]. Seismic facies consist of reflection groups differing in seismic attributes from adjacent units [2]. Seismic facies analysis is important for elucidating subsurface geology and identifying potential hydrocarbon reservoirs [3, 4]. Machine learning (ML) techniques, including neural networks and clustering algorithms, have emerged as notable tools for automated facies segmentation. The integration of multi-attribute analysis and machine learning algorithms has enabled more robust and efficient facies classification [5].

Machine learning can open new doors to exploring our geologic past and increase our understanding of smaller-scale events and processes. It can aid us in identifying and characterizing features of interest that were previously hidden in the data, while geological constraints can further improve the credibility of automated seismic facies classification [6]. However, one obstacle lies in the interpretability of certain machine learning models, which may appear as "black boxes" to geoscientists, thus complicating the comprehension of the reasoning behind predictions. Deep learning is a subset of ML and has emerged as an effective tool for automatic seismic interpretation, enabling the extraction of complex subsurface patterns and improving seismic facies analysis [7, 8].

Recently, researchers have conducted numerous studies on the Niger Delta basin using seismic and well log data, including 3D structural modelling and fluid identification [9], three-dimensional reservoir characterization and hydrocarbon volumetric estimation [10], deepwater turbidite facies and reservoir property prediction [11], seismic attribute analyses for structural configuration and hydrocarbon prospectivity [12, 13], sedimentary facies analysis of the Agbada Formation [14], and deep learning-based seismic facies classification [7, 8]. Structural modelling and spectral decomposition analyses have also been applied to characterize offshore and onshore Niger Delta fields [15, 16]. Previous research on the Ataga field includes integrated modelling and reservoir characterization [17], characterization of R8-reservoir zone in the Ataga Field [18], modelling hydrocarbon generation and biodegradation risk in Ataga oil field [19], and seismic interpretation and petrophysical analysis for evaluation of Ataga Field [20]. Machine learning (ML) has also been utilized to characterize the Niger Delta Petroleum Basin, ranging from seismic facies analysis to reservoir prediction using ML [3]. However, these studies are limited by the incomplete delineation and characterization of the geological features due to the absence of complete seismic parameters or poor consideration of the influence of thickness on amplitude. This work aims to identify machine learning models that can effectively classify the seismic facies of the Ataga Field in the Niger Delta Basin. This was achieved using Convolutional Neural Network deep learning models as implemented in the OpendTect Pro Licensed Software [21]. CNNs have demonstrated strong capability in learning hierarchical seismic features for automated seismic facies classification and interpretation [22].

Therefore, the specific objectives of this study are to analyze and identify the computational and geological classification accuracy of LeNet, ResNet18 and SimpleNet CNN models. The novelty of this study lies in the development of an integrated seismic facies characterization framework that utilizes supervised learning classification to achieve end-to-end facies prediction within the Ataga Field of the Niger Delta Basin. The workflow uniquely transforms data-driven seismic facies clusters into geologically validated training labels through Thalweg tracking and subsequently employs Convolutional Neural Networks to automate facies prediction across the seismic volume. By bridging predictive facies classification of the CNN models, the study provides a robust and scalable approach for seismic facies analysis in complex deltaic environments.

2 Geology of the Study Area

The Niger Delta Basin (Figure 1), located at the apex of the Gulf of Guinea on the west coast of Africa, is a highly productive basin characterized by a regressive clastic sequence. Positioned at the convergence of the Benue Trough and the South Atlantic Ocean, a triple junction emerged during the separation of South America and Africa in the Jurassic period [23]. This geological event resulted in the subsidence of the African continental margin and the cooling of the newly formed oceanic lithosphere as the continents continued to drift apart into the early Cretaceous era. Subsequently, during the mid-Cretaceous period, significant marine sedimentation occurred in both the Benue Trough and the Anambra basin. The early Niger Delta is interpreted as a delta dominated by river processes, whereas the post-Oligocene delta is recognized as a wave-dominated delta with well-developed shoreface sands, beach ridges, tidal channels, mangroves, and freshwater swamps. As one of the largest deltas globally, it exhibits a gradual transition from marine shales (Akata Formation) to a sand-shale paralic sequence (Agbada Formation) and finally to continental sands (Benin Formation). The delta underwent phases of regressions and transgressions due to fluctuations in sea levels, local subsidence, and sediment input [24].

Akata Formation has an age between Paleocene to Recent, with lithological composition that is majorly shale and silts with streaks of turbidite sand. However, the Agbada Formation is composed of intercalations of sands and silts with shale stacked in a prograding pattern. The age of this Formation is between Eocene and Pleistocene, and its environment of deposition is fluvial-delta. The Benin Formation's age ranges from Oligocene to Recent, and outcrops as the present delta surface. The lithology of the Benin Formation is primarily composed of sand and has been interpreted to be deposited in an alluvial or coastal plain environment [25, 26].

The tectonic framework of the Niger Delta Basin is controlled by Cretaceous fracture zones expressed as trenches and ridges in the deep Atlantic. These fracture zone ridges subdivide the continental margin into individual basins. Sediment deposition within the basin was accommodated in five (5) off-lapping siliciclastic sedimentation cycles corresponding to depobelts [27]. The depobelts consist of sediment bands approximately 30–60 km wide, prograding southwestward up to 250 km, and containing fault-bounded sequences with shoreface sand/shale alternations. These sequences are delineated at the proximal end by a major boundary growth fault and at the distal end by lithofacies changes, counter-regional growth faults, or boundary faults of subsequent depobelts. Each successive depobelt seaward contains sedimentary fills younger than those landward. Five major depobelts are generally recognized, namely, Northern Delta, Greater Ughelli, Central Swamp, Coastal Swamp, and Offshore. The most striking structural features of the Niger Delta are the large syn-sedimentary growth faults, rollover anticlines, and shale diapirs, which deformed the delta complex [24]. The sedimentary deposits in this region have an average thickness of 12 km, covering approximately 140,000 km^2 of the Akata, Agbada, and Benin formations [28].

The development of the delta structure since the Middle Eocene era has been primarily influenced by growth-faulting and associated rollover in the shelf region. According to Amigun & Akinleye-Martins [29], growth faults play a significant role as the main pathway for migration and the key factor governing the distribution of hydrocarbons in the Niger Delta. Their research study in the onshore region of the Niger Delta, an area identified to be situated within a zone where the physiographic configuration is predominantly influenced by extensional tectonic elements and the depositional processes are controlled by structural growth mechanisms such as mud diapirs and growth faults. This suggests that the region might have undergone multiple stages of tectonic activity, resulting in the formation of numerous unconformities and a substantial number of faults and fracture networks within the Agbada Formation. The fractures generated by structural movements are associated with a specific local tectonic event, forming intricate networks that exhibit distinct spatial relationships with folds and faults. The study delineated the orientations of fractures and subtle faults within low-permeability siliciclastic reservoirs, which are intricate structural features that lie well below the resolution of seismic imaging, making them challenging to detect on seismic profiles.

The stratigraphic framework and detailed Tertiary stratigraphy of the Niger Delta rely on the correlation of palynomorphs and foraminifera zones [24]. The lithostratigraphic units underlying the Niger Delta, namely the Akata, Agbada, and Benin Formations, are illustrated in Figure 2.

The petroleum system identified in this area is primarily the Tertiary Niger Delta petroleum system. This system is sourced by two main contributions from the Akata Formation and interbedded shale in the lower Agbada Formation, resembling the marine Akata Formation. The turbidite sands found at the Akata Formation's top are considered potential reservoirs in deep water, as this Formation originated during low stands, making terrestrial structural traps the primary focus of exploration [24]. Trap types are mainly dip closures. Smaller oil and gas fields are associated with stratigraphic traps. The seal rock is primarily interbedded marine shales within the Agbada formation. The three types of seals

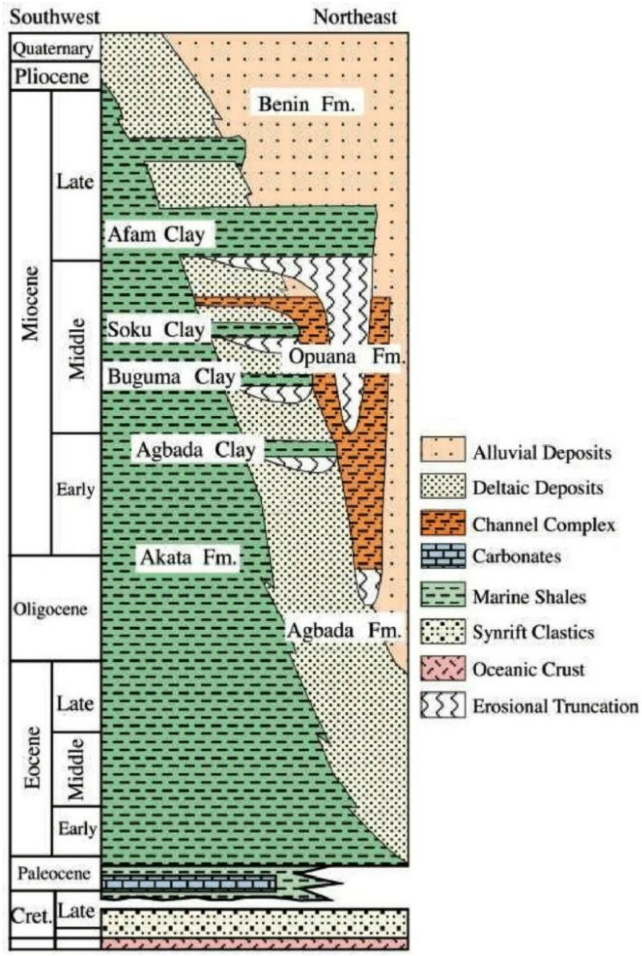

Figure 2. Stratigraphy of Niger Delta [30].

are: smearing of clay along faults, vertical seals and interbedded sealing layers against which subsurface reservoir sands juxtapose because of faulting [25].

The study area is within the Ataga Field located offshore the Niger Delta, Nigeria. The Niger Delta is located in the Gulf of Guinea, on the West Africa Margin and spreads all through the Niger Delta province between longitude 5°E to 8°E and latitude 4°N to 6°N [31]. The location of the Ataga field is shown in Figure 3. The Ataga field reservoir sand units have good porosities, permeability and hydrocarbon saturation index, indicating that they have good hydrocarbon potential [18]. The reservoir is characterized by quite large amplitudes in some regions. The Root mean square (RMS) amplitude exhibited a high amplitude and bright spot (DHI) area around the structural highs [20]. The structures identified are mainly growth faults with rollover anticlines and are the dominant traps [17]. These growth faults have associated synthetic and antithetic faults, which are listric in nature. These listric faults are syndepositional, exhibiting an increase in stratigraphic thickening on the downthrown block as shown by the bright and distinct signature on this side [17, 20].

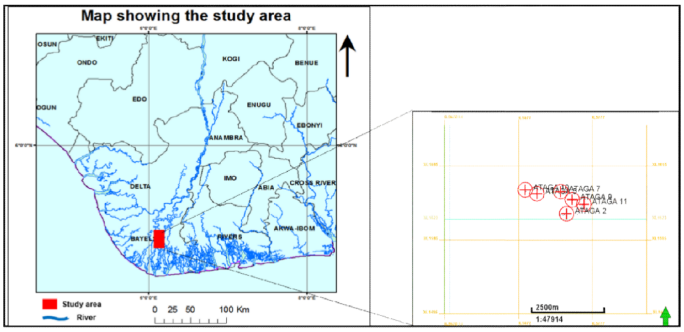

Figure 3. Location and base map of the area [18].

The lithologic units have a general lateral continuity over the field, as shown by stratigraphic trends. All of the wells were discovered to have hydrocarbon-bearing reservoir formations (sandstones) and are mostly oil-bearing zones [20]. The variation of sand to shale ranges from 40% - 60%. This shows that the reservoir sands present in the field are minimal [17]. However, in another study, the result of R8-reservoir facies modelling was reported to indicate a high sand-to-shale proportion with intercalated silts [18]. The study observed facies within the wells consists of channels, barrier bars complexes, delta-marine fringes and a few mudstones. However, the environments of deposition/facies delineated include channels, shoreface sands (upper and lower shorefaces), heterolithics and shales [18].

3 Theory

Supervised seismic facies analysis requires that labels of the seismic facies are available as inputs to the machine learning network. Supervised learning for seismic facies classification is an established seismic interpretation method [32–34]. Supervised classification has been used effectively in seismic facies analysis to delineate seismic facies in different complex sedimentary formations. It uses the facies labels to study the input data pattern and thereby predict the seismic facies classes accordingly. For example, De Groot et al. [32] used Image-to-Point methods to show a supervised seismic facies classification. Their target was an interval with stacked meandering channels deposited during the Miocene. They presented their supervised classifications at two stratigraphic levels in the Wheeler domain (flattened seismic domain). Similarly, Yang et al. [34], developed a fast and effective automatic seismic facies interpretation scheme using supervised deep learning. The model improves seismic facies classification on the F3 public data set with detailed information. The applicability of supervised machine learning to seismic facies analyses on the 3D seismic reflection data of the northern North Sea rift was demonstrated by Wrona et al. [33]. Applying their model to an entire seismic section shows that it was able to provide a robust seismic facies analysis.

In this study, we employ a Thalweg tracker method to create the label data in the form of a point set. We adopted the Thalweg tracker at the expense of Manual and paintbrush tracking because of its ability to track samples at the reservoir scale level, which is exactly the requirement for seismic facies classification [21].

A Thalweg is a geological term used to describe the natural path a river follows as it flows through a valley. It essentially traces the line of lowest elevation or least resistance. The Thalweg tracker works on a similar principle in seismic data: it follows the path that best matches the data characteristics at each

Table 1. Summary of Thalweg Tracker–derived pointset labels used for supervised seismic facies classification.

Facies Type	Amplitude Condition	Training Samples	Facies Color (as shown in Figure 4)
Channel Sand	Minima	1500	Cyan
Channel Sand	Maxima	1500	Violet
Heterolithic Sand	Minima	1500	Purple
Heterolithic Sand	Maxima	1500	Green
Heterolithic Shale	Minima	1500	Blue
Heterolithic Shale	Maxima	1500	Red
Shale	Minima	1500	Dark blue
Shale	Maxima	1500	Lavender
Shoreface	Minima	1500	Magenta
Shoreface	Maxima	1500	Yellow

step. In practice, the tracker is used to map 3D geological bodies or horizons, especially for detailed seismic facies interpretation. It works by progressively extending from an initial starting point (called a seed), which is defined by the user within the seismic volume. From this seed point, the algorithm examines the immediately neighbouring samples and selects the one that best matches the tracking criteria. This newly selected point is then added to the tracked path. The process repeats iteratively—each time considering neighbouring samples around all previously accepted points and adding only the best match. The tracking continues step by step until no further neighbouring samples satisfy the defined constraints, at which point the process stops [21].

The Thalweg tracker was used to track facies that were clustered in the Unsupervised Vector Quantizer Network (UVQ). The UVQ clustered the input seismic cube constrained target interval into five (5) clusters. The identified five clusters are then interpreted based on their reflection geometries and validated using log responses. The interpreted facies are: channel sand, shale, heterolithic sand, heterolithic shale and shoreface [18, 24]. Now, the Thalweg tracker was used to track the training samples set. The Thalweg tracker has the capability of tracking both maximum and minimum amplitudes for each facies. Each of the five depositional facies identified in the UVQ clustering was represented under both minima and maxima amplitude conditions, resulting in ten balanced classes. Each class contains 1500 training samples, ensuring uniform representation across facies and amplitude responses for robust model training. The pointset labels are shown in Figure 4 and Table 1.

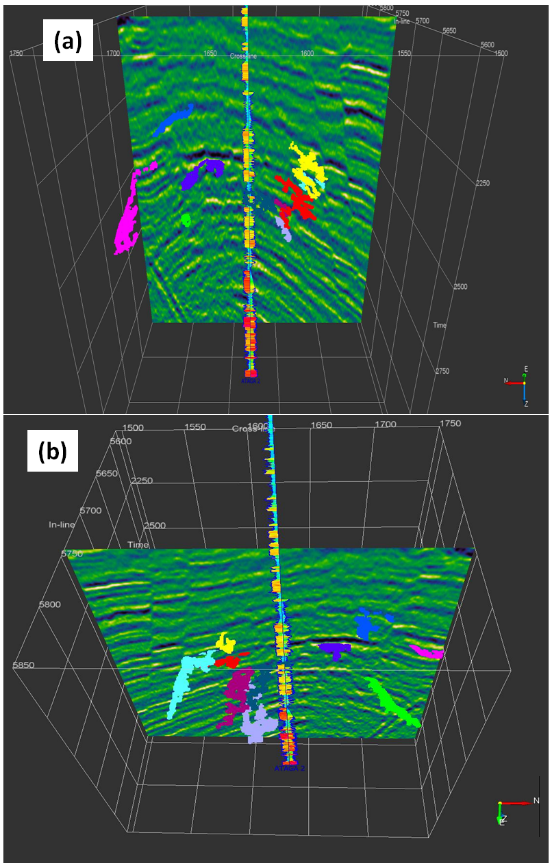

Figure 4. Thalweg tracked facies labels on inline 5746, (a) front view, and (b) back view.

4 Materials and methods

4.1 Field data

The available Ataga oil field data include well header, well logs, well deviation survey, seismic and checkshots data. The seismic data is a 3-D seismic reflection data and a suite of well logs from Ataga 2 Well in Ataga Field, shallow offshore, Niger Delta Basin, Nigeria. Supervised machine learning and metric calculations were carried out with an infrastructure powered by OpendTect Machine Learning Plugin. Log plots from the Ataga-2 Well were used to validate the seismic facies classification. The workflow of the supervised learning is illustrated in Figure 5.

4.2 Computational Method

All supervised classification models were implemented within the OpendTect machine learning environment using the Keras deep learning platform. The workflow employed three CNN architectures: LeNet, ResNet18, and SimpleNet. The architectures were trained individually under a consistent set of computational parameters to enable objective performance comparison.

The input dataset comprised seismic amplitude volumes of the generated dip-steered median filter (DSMF), with training labels derived from ten facies classes (minimum and maximum representations) interpreted from horizon-constrained intervals. For each labelled point, cubelets of size $41 \times 41 \times 3$ samples were extracted to capture both lateral and vertical seismic context, as shown in Figure 5.

Prior to training, all input data were subjected to Global Standardization, ensuring zero mean and unit variance across the dataset to stabilize convergence and improve model generalization. Training was performed for a maximum of 15 epochs using a batch size of 32, while an early stopping criterion with a patience of

10 epochs was applied to prevent overfitting. The optimization process employed a learning rate of 0.0001 with a learning rate decay factor applied every 5 epochs, and the dataset was split into training and validation subsets using a ratio of 80:20. A five-fold cross-validation strategy was incorporated to improve model robustness and generalization. Mixed precision (FP16) computation was enabled to enhance training efficiency, and GPU-accelerated training was utilized.

4.3 CNN Architectures

4.3.1 LeNet CNN Architecture

LeNet is a convolutional neural network designed to learn hierarchical feature representations directly from raw input data using gradient-based optimization. The process begins with an input image (2D or 3D), which is passed through a sequence of convolutional layers. These layers apply learnable filters to extract local spatial features such as edges, textures, and patterns. Each convolutional stage is followed by a non-linear activation function, enabling the network to model complex relationships in the data.

After convolution, sub-sampling (pooling) layers reduce the spatial dimensions of the feature maps while preserving the most relevant information. This step introduces translation invariance and reduces computational complexity. As the data progresses deeper into the network, the learned features become increasingly abstract and representative of higher-level structures.

The final stages of the network consist of fully connected layers, where the extracted features are combined to form a global representation. The last layer produces output scores corresponding to each class, which are converted into probabilities (typically via a softmax function). During training, the network parameters are optimized using backpropagation, where prediction errors are propagated backward through the network and weights are updated using gradient descent [38]. The workflow of the LeNet architecture is illustrated in Figure 6. This LeNet architecture is inbuilt in the OpendTect Machine Learning Plugin and was selected for the supervised learning, the training parameters are adjusted as discussed in section 4.2.

4.3.2 ResNet-18 CNN Architecture

The ResNet-18 CNN architecture in Figure 7 operates using a residual learning framework that enables efficient training of deep networks through identity-based skip connections. Instead of learning a direct mapping, the network learns residual functions, allowing the input to be added back to the output of convolutional layers. This approach improves gradient flow and prevents performance degradation with depth, as described by He et al. [36].

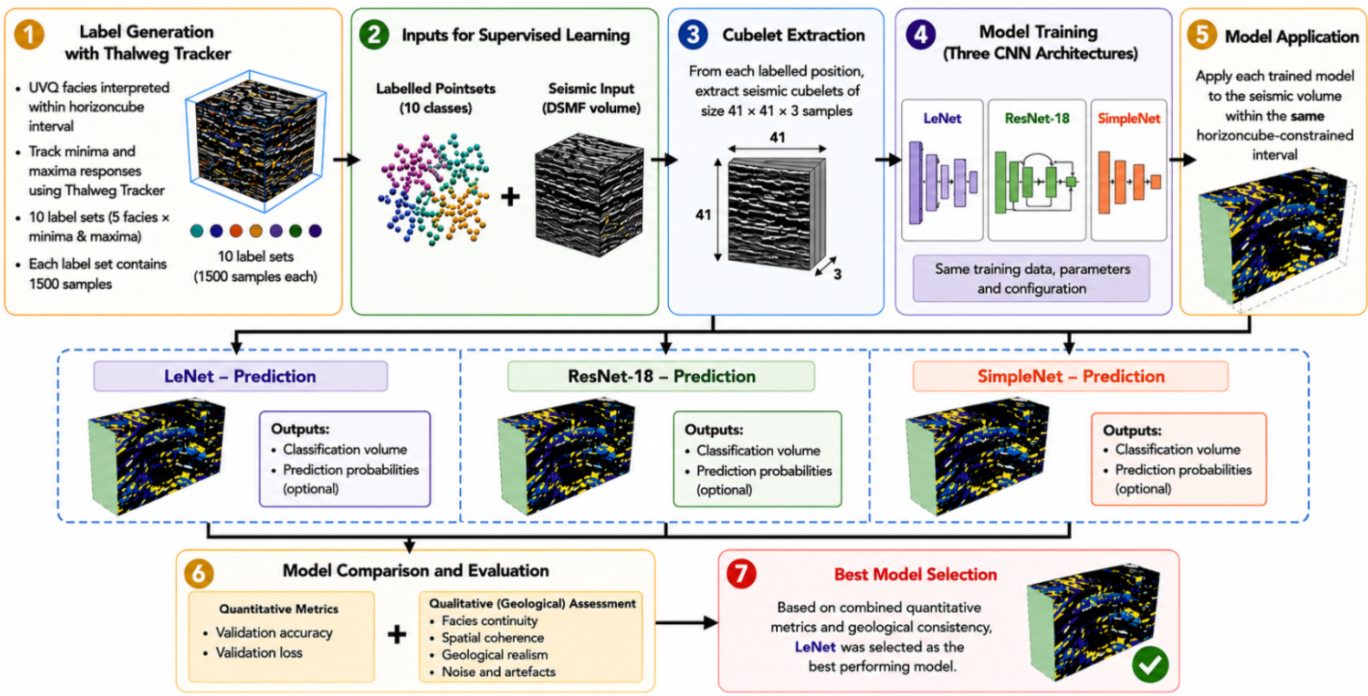

Figure 5. Workflow adopted for Supervised seismic facies classification in the Ataga Field. The methodology integrates labels extraction using Thalweg tracker, cubelets extraction, CNN models training and application, models comparison and evaluation.

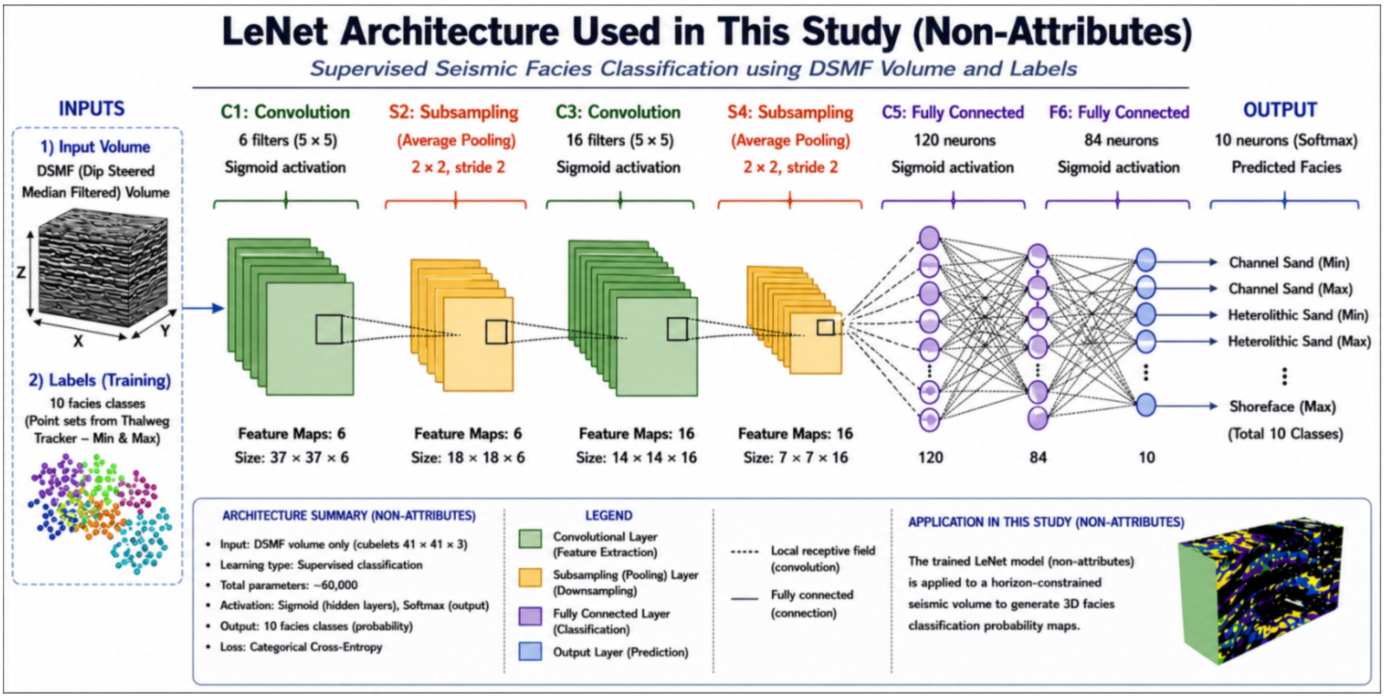

Figure 6. Simplified LeNet CNN architecture workflow showing supervised facies classification using DSMF seismic input and labeled cubelets, from feature extraction through convolutional layers to final prediction output.

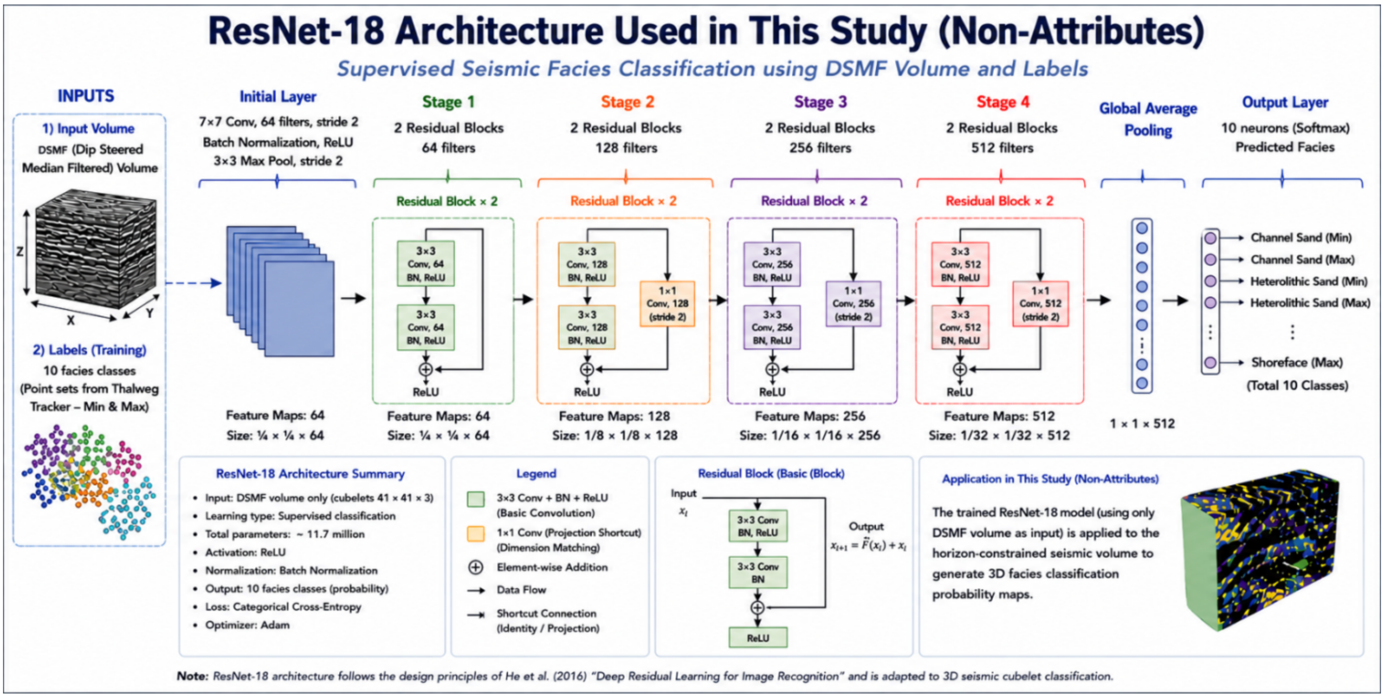

Figure 7. Workflow of the ResNet18 CNN architecture for supervised seismic facies classification using DSMF seismic input and Thalweg-derived labels.

The model begins with an initial convolution and pooling stage for low-level feature extraction, followed by four stages of residual blocks. Each block consists of two convolutional layers with nonlinear activation, combined with a shortcut connection that preserves the original input information. Through these stacked blocks, the network progressively learns hierarchical features, from basic seismic textures to complex facies patterns.

A global average pooling layer is then applied to condense the feature maps, and the resulting features are passed to a fully connected layer with softmax activation to produce class probabilities. During training, backpropagation is used to optimize the network, with residual connections ensuring stable convergence. In seismic applications, this architecture enables improved representation of subtle stratigraphic variations while maintaining continuity of the original signal [36]. This ResNet18 architecture is built into the OpendTect Machine Learning Plugin and was selected for the supervised learning; the training parameters are adjusted as discussed in section 4.2.

4.3.3 SimpleNet CNN Architecture

The SimpleNet CNN architecture shown in Figure 8 represents a shallow CNN designed for efficient feature extraction with reduced architectural complexity. The model operates by passing the input data, in this case seismic cubelets, through a sequence of convolutional layers combined with nonlinear activation functions to capture local spatial patterns such as amplitude variations, textures, and reflector geometries. Periodic pooling operations are applied to downsample the feature maps, thereby reducing dimensionality while retaining the most informative features.

As the network depth is limited, feature learning remains relatively direct, with intermediate representations capturing low- to mid-level seismic characteristics. The extracted features are subsequently flattened and forwarded to fully connected layers, where they are integrated into a global representation for classification. The final output layer employs a softmax function to generate class probabilities corresponding to the predefined facies categories. Training is performed using backpropagation and gradient-based optimization, enabling the model to iteratively refine its parameters [35]. This SimpleNet architecture is built into the Opendtect Machine Learning Plugin and was selected for the supervised learning; the training parameters are adjusted as discussed in section 4.2.

5 Computational Results

Figure 9 shows the Horizoncube constrained DSMF seismic cube together with the Ataga 2 GR and RHOB log overlaid. The cube volume ranges between inline 5746-5800, crossline 1500-1750 and Z slice of 2288 - 2824ms. All the trained CNN models were applied to this volume for effective seismic facies classification and comparison.

The DSMF volume reveals laterally continuous to moderately discontinuous reflectors, indicative of interbedded sand–shale sequences. The presence of undulating reflector geometries, lateral terminations, and localized amplitude anomalies suggests a channelized to shoreface depositional system. High-amplitude, laterally persistent reflections are interpreted as sand-prone units, while lower amplitude and less continuous reflections correspond to heterolithic and shale-dominated facies. Vertical stacking patterns indicate repetitive depositional cycles, likely reflecting progradation and channel migration processes. GR variability aligns with seismic layering, RHOB contrasts correspond to strong reflectors, which confirms lithology-driven reflectivity. The trained seismic facies classification CNN models as applied to the DSMF cube are shown in Figure 10.

The LeNet model exhibits laterally continuous and stratigraphically coherent facies distributions that conform closely to seismic reflectors and well log responses. In contrast, the ResNet18 output shows moderate fragmentation and reduced continuity, while the SimpleNet result is characterized by pronounced patchiness, poor lateral connectivity, and geologically unrealistic facies variability. These visual differences highlight the varying ability of each model to preserve subsurface geological architecture.

The performance of the three CNN architectures—LeNet, ResNet18, and SimpleNet—was evaluated using both quantitative training metrics and qualitative geological assessment of the classified seismic volume. While all models demonstrated progressive improvement during training, their predictive behaviours differ significantly when applied to the 3D seismic cube.

A more rigorous evaluation was therefore conducted by examining the spatial distribution and geological plausibility of the predicted facies within the classified cube. The LeNet model demonstrates superior performance in this regard. Its output preserves key seismic characteristics, including reflector continuity, stratigraphic layering, and depositional geometries. Facies bodies are laterally continuous and conform to the structural dip of the reflectors, indicating that the model successfully captures spatial dependencies inherent in seismic data. Furthermore, channel-like features appear coherent and connected, consistent with expected depositional patterns within the Agbada Formation. Importantly, the facies transitions along the well trajectory are gradual and correlate well with gamma ray (GR) and bulk density (RHOB) log responses, reinforcing the reliability of the classification.

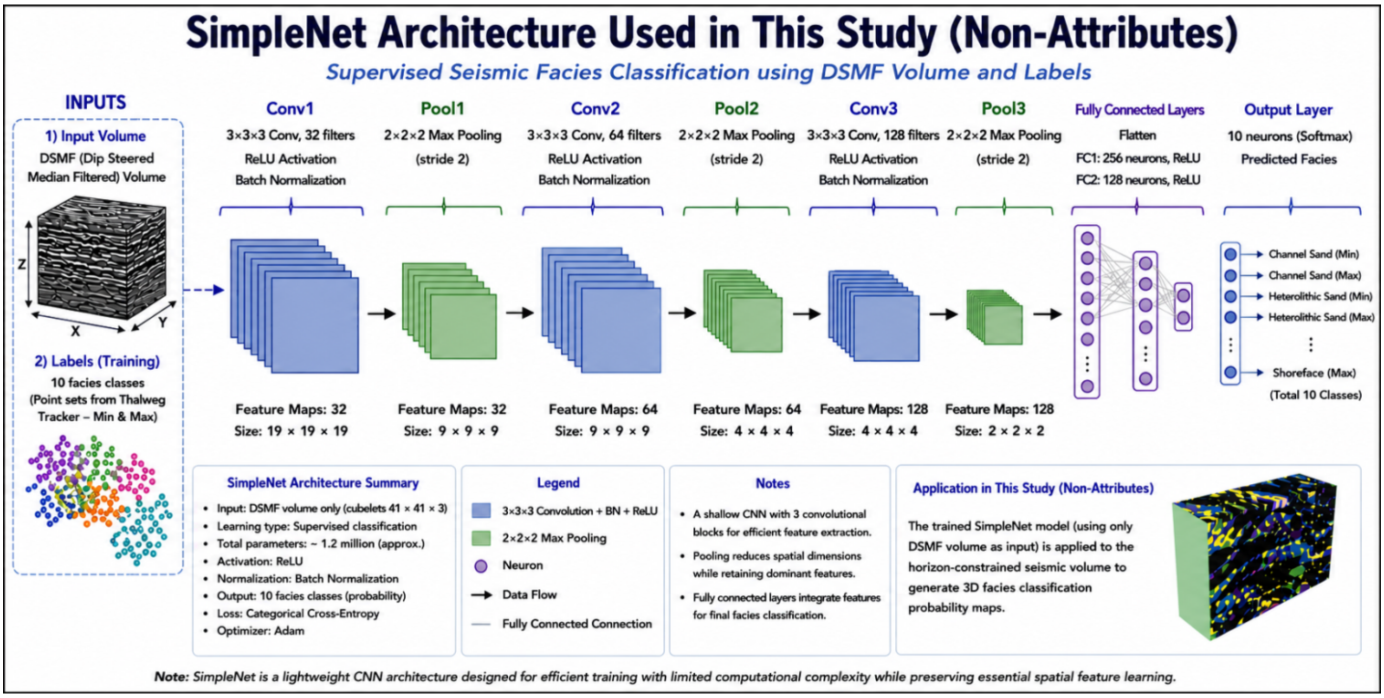

Figure 8. Workflow of the SimpleNet convolutional neural network architecture for supervised seismic facies classification using DSMF seismic input and thalweg-derived labels.

In contrast, the ResNet18 model, although achieving high validation accuracy, exhibits moderate degradation in geological quality. While large-scale layering is still recognizable, facies bodies show increased fragmentation and reduced lateral continuity. Channel geometries appear partially disconnected, and the classification introduces noticeable noise, suggesting that the model may be overfitting to local seismic textures rather than learning broader stratigraphic patterns. Although ResNet18 incorporates residual learning to facilitate deeper feature extraction [36], its increased architectural complexity does not necessarily translate into superior performance for relatively small seismic training datasets. Previous studies have shown that deeper CNN architectures require compound scaling of depth, width, and resolution to achieve performance gains, which incurs significantly higher computational costs [37], making lightweight architectures such as LeNet more practical for limited training datasets.

The SimpleNet model performs poorly when evaluated against geological criteria. Its classification output is characterized by significant patchiness, with facies distributed in a highly fragmented and discontinuous manner. The absence of coherent layering and the presence of erratic facies switching, particularly along the well trajectory, indicate that the model fails to capture the spatial continuity of subsurface geology. This behaviour is typical of shallow architectures that lack the representational capacity to model complex seismic patterns. As a result, the SimpleNet

Table 2. Comparative geological evaluation of the predicted seismic facies volumes generated by the LeNet, ResNet18, and SimpleNet convolutional neural network architectures.

Criterion	LeNet	ResNet18	SimpleNet
Reflector Conformity	Excellent	Good	Moderate
Facies Continuity	Excellent	Moderate	Moderate
Facies Fragmentation	Low	Moderate	High
Agreement with Well Logs	Strong	Moderate	Moderate
Geological Interpretability	High	Moderate	Moderate

Table 3. Epoch-wise comparison of validation accuracy and validation loss for LeNet, SimpleNet, and ResNet18 models.

Epoch	LeNet		SimpleNet		ResNet18	
	Val Acc	Val Loss	Val Acc	Val Loss	Val Acc	Val Loss
1	0.3068	1.8669	0.3302	1.9773	0.5495	1.7411
2	0.8875	0.7657	0.8989	0.7705	0.8762	0.7492
3	0.9224	0.5886	0.9199	0.5856	0.9064	0.5604
4	0.9139	0.5109	0.9409	0.4810	0.9431	0.4627
5	0.9445	0.4212	0.9395	0.4457	0.9569	0.4234
6	0.9566	0.3883	0.9520	0.3966	0.9448	0.3817
7	0.9633	0.3306	0.9495	0.3783	0.9580	0.3475
8	0.9690	0.2993	0.9534	0.3378	0.9488	0.3267
9	0.9680	0.2628	0.9601	0.3170	0.9701	0.2969
10	0.9726	0.2562	0.9811	0.2785	0.9733	0.2883
11	0.9779	0.2381	0.9744	0.2735	0.9740	0.2704
12	0.9719	0.2416	0.9776	0.2661	0.9776	0.2569
13	0.9794	0.2195	0.9801	0.2527	0.9751	0.2454
14	0.9794	0.2068	0.9765	0.2526	0.9794	0.2463
15	0.9833	0.2038	0.9811	0.2367	0.9747	0.2380

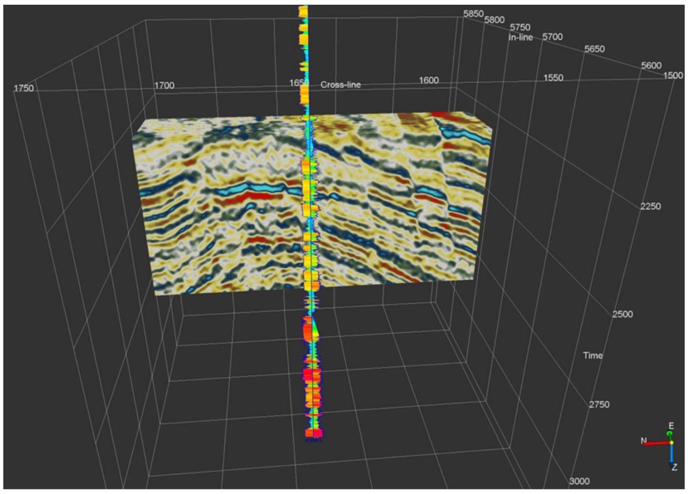

Figure 9. Horizoncube constrained DSMF seismic cube together with the Ataga2 GR and RHOB log overlaid. The cube ranges between inline 5746-5800, crossline 1500-1750 and Z slice of 2288ms - 2824ms.

output is considered geologically poor. Table 2 presents a summary of the geological comparison of the three CNN models. Table 2 shows that LeNet consistently produced the most geologically coherent facies distribution, characterized by superior reflector conformity, lateral continuity, stratigraphic consistency, and agreement with well-log responses, thereby justifying its selection as the preferred model for seismic facies classification.

5.1 CNN Models Computational Metrics

The model's performance was assessed using validation accuracy and validation loss over 15 training epochs, with emphasis placed on generalization capability rather than training performance, as shown in Table 3. All three models demonstrated rapid convergence within the first few epochs, reflecting the strong separability of the UVQ facies labels used as input. However, clear differences emerged in their stability and final performance. The LeNet architecture consistently exhibited the most stable learning behaviour, with a generally monotonic decrease in validation loss and minimal oscillations in validation accuracy after convergence. It achieved the highest validation accuracy (0.9833) and the lowest validation loss (0.2038) at the final epoch, indicating superior generalization and robustness.

SimpleNet also performed strongly, reaching a comparable validation accuracy (0.9811) but with slightly higher validation loss (0.2367) and minor fluctuations during later epochs, suggesting a marginally reduced stability relative to LeNet. In contrast, ResNet18, despite its deeper architecture, yielded the lowest performance among the three models, with a final validation accuracy of 0.9747 and validation loss of 0.2380. The comparatively lower performance of ResNet18 is attributed to the relatively structured and moderately complex nature of the seismic dataset, where simpler architectures are sufficient to capture the underlying feature representations without the risk of over-parameterization. These results highlight that increasing architectural complexity does not necessarily translate to improved performance in seismic facies classification tasks. Instead, model suitability is strongly dependent on data

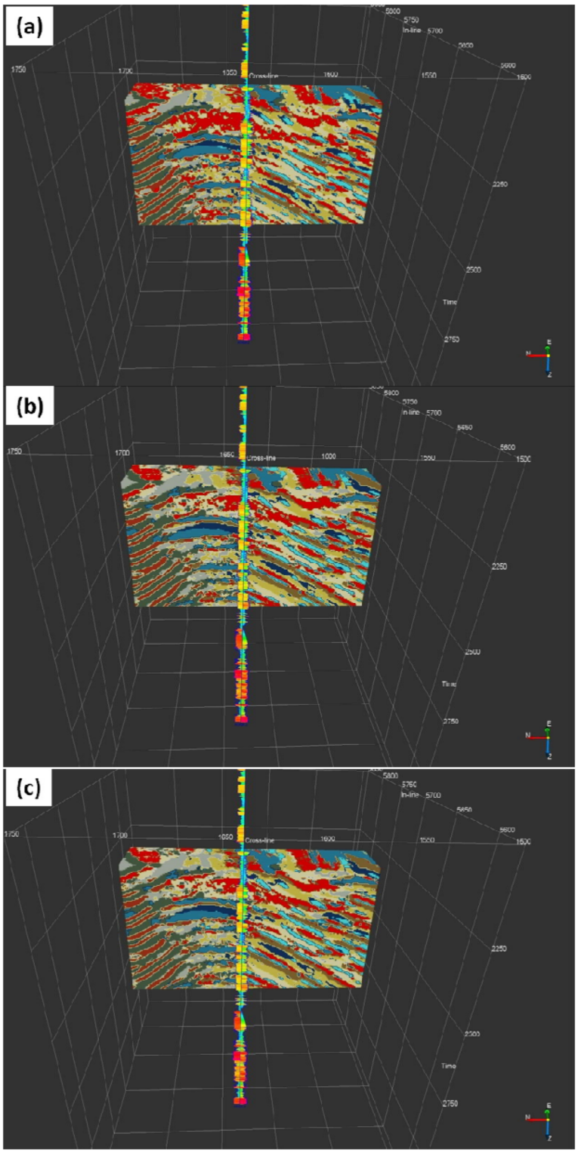

Figure 10. Three-dimensional seismic facies classification results generated using (a) LeNet, (b) ResNet18, and (c) SimpleNet CNNs over the same horizon-constrained cube (Inline 5746–5800, Crossline 1500–1750, Z-depth 2288–2824 ms), with the Ataga-2 well overlaid for validation.

characteristics. Based on the observed validation metrics and convergence behaviour, the LeNet model was selected as the optimal architecture for subsequent facies prediction and interpretation. As presented in Table 3, LeNet demonstrates the most stable convergence and superior generalization performance, achieving the highest validation accuracy and lowest validation loss at the final epoch.

Among the evaluated CNN architectures, the LeNet model demonstrated superior generalization performance, achieving the highest validation accuracy and lowest validation loss, and producing geologically meaningful results, indicating its suitability for the given seismic facies classification problem.

5.2 Lenet Supervised Seismic Facies Classification

The LeNet classification cube shown in Figure 11 (a) demonstrates a clear correspondence between predicted facies and seismic reflector geometry, with laterally continuous facies bodies that align with the stratigraphic architecture observed in the DSMF volume. While the model successfully differentiates major lithofacies groups, partial merging of minima and maxima classes suggests limited sensitivity to polarity variations, though overall depositional patterns remain geologically consistent. The reduced sensitivity to polarity variations is attributed to the fact that seismic reflections of opposite polarity often represent the same geological interface and therefore exhibit similar spatial textures and reflector geometry. Consequently, the CNN learned to emphasize lithological and stratigraphic features rather than polarity differences. Furthermore, DSMF preprocessing enhanced reflector continuity, reducing subtle polarity variations while preserving the overall geological architecture.

Validation against well log data, shown in Figure 11 (b), indicates that the LeNet-derived facies classification exhibits a strong correspondence with lithological variations, where low gamma-ray intervals align with sand-prone facies and high gamma-ray intervals correspond to shale-dominated classes. Transitional log responses are reflected by intermediate facies, confirming that the model successfully captures subsurface heterogeneity. Minor inconsistencies are observed at finer scales, likely due to limited separability between polarity-based label pairs.

6 Discussion

The DSMF seismic volume [21] exhibits well-defined, laterally continuous reflectors with moderate undulations and localized discontinuities. These reflectors form organized stratigraphic packages characterized by alternating high- and low-amplitude responses. High-amplitude, laterally persistent reflections are interpreted as delta sand-prone units [39], whereas lower amplitude and less continuous reflections correspond to heterolithic and shale-dominated intervals.

The reflector geometry shows sigmoidal and undulating patterns, along with subtle terminations and thickness variations, suggesting a channelized to shoreface depositional system. Vertical stacking

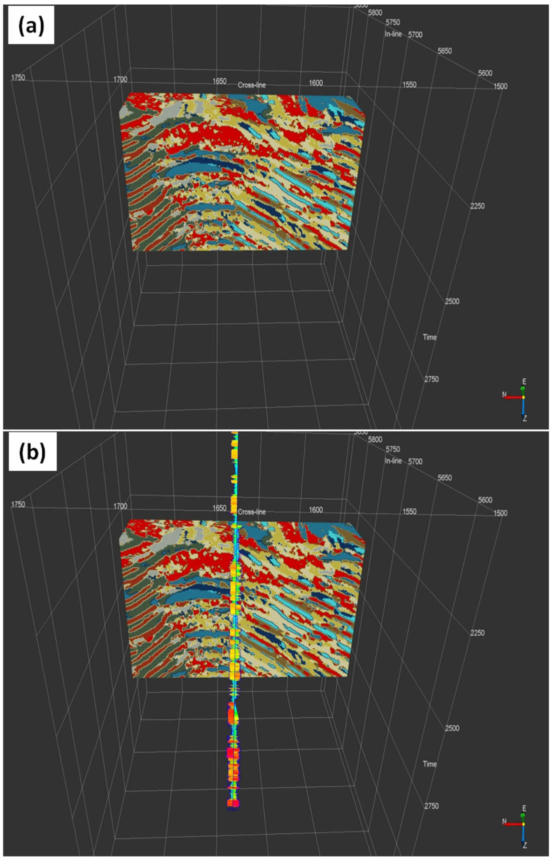

Figure 11. LeNet-derived facies classification cube showing laterally continuous, stratigraphically consistent facies distribution aligned with DSMF seismic reflectors (a) without, and (b) with the well log inserted.

of reflectors indicates repetitive depositional cycles, likely reflecting progradation and lateral migration processes. Related studies [7, 12, 17, 18, 20, 39] reported similar geological features. This suggests that the DSMF filtering effectively enhances reflector continuity while preserving geological features, providing a reliable foundation for subsequent facies classification. The improved reflector continuity illustrates that DSMF filtering successfully suppresses incoherent noise while preserving structural and stratigraphic information. This enhancement provides more discriminative seismic textures for CNN feature extraction, thereby improving the reliability of subsequent facies classification.

The LeNet classification cube, trained using DSMF input and ten facies label sets derived from interpreted UVQ clusters, reveals a geologically coherent facies distribution. The predicted facies exhibit strong alignment with seismic reflector geometry, forming laterally continuous and stratigraphically consistent bands across the volume. Distinct facies bodies are observed, including a prominent, laterally continuous unit interpreted as a channel sand, surrounded by more heterogeneous facies indicative of heterolithic deposits. More uniform zones correspond to shale-dominated intervals, consistent with the baseline seismic interpretation [39].

Importantly, all facies classes are represented in the volume, confirming that the model successfully learned the variability encoded in the training labels. However, partial merging of facies pairs, particularly those defined by minima and maxima polarity, suggests that the model is more sensitive to lithological contrasts than to polarity-based distinctions. This results in localized dominance of certain facies (notably red-colored classes) and minor over-fragmentation in some intervals. Despite these limitations, the classification preserves lateral continuity and depositional architecture, indicating that the model effectively captures the underlying geological patterns rather than producing random or noisy predictions.

Integration of well log data provides critical validation of the predicted facies. A strong correspondence is observed between the classification results and lithological indicators. Low gamma-ray (GR) intervals, indicative of cleaner sands, align predominantly with sand-prone facies (e.g., blue/teal classes). High GR intervals, associated with shale-rich zones, correspond to shale-dominated facies (e.g., red classes). Intermediate GR responses are reflected by mixed or transitional facies, representing heterolithic deposits. Density (RHOB) variations further support these interpretations, with contrasts aligning with major reflector boundaries and facies transitions. The vertical succession of predicted facies closely follows log trends, demonstrating that the model captures true lithological variability rather than purely seismic texture. Our analysis of the lithofacies (sandstones and shales) compares well with other interpretation results in the Ataga Field [17, 18, 20].

However, some intervals exhibit multiple facies assignments within similar log responses, indicating minor over-sensitivity of the model, likely due to limited separability between closely related classes (e.g., minima vs. maxima labels). Nevertheless, no systematic misclassification is observed, and the overall agreement remains robust.

The combined analysis of seismic character, facies classification, and well log validation demonstrates that the LeNet model successfully translates seismic patterns into geologically meaningful facies distributions. The workflow effectively captures: depositional architecture, comprising channelized and layered systems; lithological contrasts that distinguish sand, shale, and heterolithic facies; and stratigraphic continuity that preserves lateral and vertical relationships. The identified channel and mouth-bar sands constitute potential reservoir units, whereas the laterally persistent marine shales provide effective sealing intervals. The environment of deposition of such reflections is normally the delta front [39].

The proposed workflow provides a practical approach for reducing interpreter subjectivity while accelerating seismic facies mapping over large 3D datasets. The integration of machine learning with geological validation enhances confidence in facies prediction and supports more efficient seismic facies analysis. The main limitation lies in the redundancy of polarity-based label pairs, which reduces class separability and introduces minor ambiguity in facies boundaries. However, this does not significantly impact the overall geological interpretation. This may be due to the fact that the CNN models were trained using labels derived from Thalweg-tracked facies interpretations, meaning that the classification quality is inherently dependent on the accuracy of the training labels. Second, the workflow was developed and validated using data from a single field within the Niger Delta Basin; consequently, its general applicability to other geological settings remains to be demonstrated. Third, only the DSMF seismic volume was used as input during model comparison, whereas incorporating additional seismic attributes may further improve facies discrimination. Finally, model evaluation relied primarily on validation accuracy, validation loss, geological consistency, and well-log agreement. Future work would be tested on independent datasets to further evaluate model robustness. Although the workflow was developed using the Ataga Field, its methodology is transferable to other sedimentary basins with comparable 3D seismic data and well control. However, because seismic facies characteristics vary between geological settings, the CNN model should be retrained using field-specific training labels to ensure reliable and geologically meaningful predictions.

7 Conclusion

Overall, the DSMF-guided LeNet classification provides a reliable and interpretable facies model that is consistent with both seismic expression and well log data. The results confirm that the adopted workflow is capable of producing high-quality subsurface facies predictions, suitable for geological interpretation and further reservoir characterization. Future work would focus on a multi-attribute LeNet CNN architecture for seismic facies classification. However, the proposed study has several limitations: 1) it was conducted on a single field; 2) the training labels were interpreter-derived, introducing potential subjectivity; 3) only the DSMF seismic volume was used as CNN input; 4) the validation metrics were limited to those available in OpendTect; and 5) the generalization of the workflow to other basins remains to be tested.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

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