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Deep Learning-Based Gravity Interpretation for Petroleum Reservoir Prediction and Prospectivity Zonation in Gongola Basin, Northeastern Nigeria

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ABSTRACT

Residual gravity anomalies provide valuable information for delineating subsurface structures and evaluating petroleum prospectivity in sedimentary basins. This study presents a deep learning framework for gravity anomaly interpretation and petroleum reservoir prediction in the Gongola Basin, northeastern Nigeria, using satellite-derived gravity data from the GOCO06s global gravity field model. Regional gravity trends were removed through spectral and polynomial filtering, while gravity derivatives were computed to enhance structural discontinuities associated with faults, depocenters, structural highs, and stratigraphic traps. An attention-enhanced U-Net convolutional neural network was developed to simultaneously reconstruct residual gravity anomalies and classify petroleum-related structural features. The predicted petroleum prospectivity map identifies the central and southwestern sectors of the Gongola Basin as the most favorable exploration targets, consistent with known structural depocenters and gravity lows. Monte Carlo dropout uncertainty analysis further indicates high prediction confidence across structurally coherent regions while highlighting areas requiring additional geophysical constraints. The proposed framework demonstrates that integrating satellite gravity data with deep learning provides a rapid, scalable, and cost-effective approach for structural interpretation and petroleum prospectivity assessment in frontier sedimentary basins.

1. INTRODUCTION

Gravity anomaly interpretation remains one of the most important geophysical techniques for subsurface structural investigation and petroleum exploration because variations in the Earth's gravity field reflect lateral and vertical density contrasts associated with sedimentary thickness, basement morphology, fault systems, folds, and structural traps (Blakely, 1995; Hinze et al., 2013; Telford et al., 1990). In frontier sedimentary basins where seismic acquisition is limited by cost or accessibility, gravity data provide an efficient and cost-effective means of regional basin evaluation, structural mapping, and hydrocarbon prospectivity assessment (Hinze et al., 2013; Lowrie and Fichtner, 2020).

The Gongola Basin, located within the Upper Benue Trough of northeastern Nigeria, is one of the major Cretaceous intracontinental rift basins in West Africa and has long been recognized for its significant hydrocarbon potential (Obaje et al., 2006). The basin evolved during the Early Cretaceous rifting associated with the opening of the South Atlantic Ocean, resulting in the development of fault-controlled depocenters, horst-graben systems, and thick sedimentary successions favorable for petroleum generation and accumulation (Benkhelil, 1989; Guiraud, 1990; Zaborski et al., 1997). Geological and geochemical investigations have demonstrated that several formations within the basin contain mature source rocks, suitable reservoir units, and structural traps capable of supporting commercial hydrocarbon accumulations (Obaje et al., 2004; Obaje, 2009). Previous gravity and structural investigations have also identified major basement faults, sedimentary depocenters, and structural closures that constitute important petroleum system elements within the basin (Fairhead and Okereke, 1987; Obaje, 2009).

Recent advances in artificial intelligence (AI) and deep learning have significantly transformed geophysical data processing and interpretation by enabling automatic extraction of complex spatial patterns from large geoscientific datasets. Deep convolutional neural networks (CNNs) have demonstrated remarkable capability in image recognition, inversion, feature extraction, and geophysical interpretation because of their ability to learn nonlinear spatial relationships directly from multidimensional data (LeCun et al., 2015; Goodfellow et al., 2016; Bergen et al., 2019). In geoscience applications, CNN-based approaches have been successfully applied to seismic interpretation, gravity inversion, geological feature extraction, and subsurface characterization, providing substantial improvements over conventional deterministic interpretation techniques (Bergen et al., 2019; Di et al., 2019).

Among deep learning architectures, the U-Net encoder-decoder network has become particularly attractive for geophysical inversion and image reconstruction because its skip-connection mechanism preserves both local and global spatial information while improving multiscale feature extraction (Ronneberger et al., 2015). Recent studies have demonstrated that U-Net-based models can accurately reconstruct geophysical data and enhance subsurface structural imaging and inversion, thereby improving the interpretation of gravity and magnetic anomalies (Li et al., 2023). In petroleum geoscience, deep learning techniques have been successfully employed for reservoir characterization, permeability prediction, facies classification, and reservoir modeling and simulation, illustrating their growing importance in hydrocarbon exploration and development workflows (Arigbe et al., 2019; Zhang et al., 2019).

Gravity anomaly interpretation continues to play a fundamental role in petroleum exploration because residual gravity anomalies often reflect variations in basement depth, sedimentary thickness, fault architecture, and structural traps that control hydrocarbon generation and accumulation (Blakely, 1995; Hinze et al., 2013). Derivative-based enhancement techniques, including vertical derivatives, horizontal gradients, and analytic signal processing, have further improved the delineation of subsurface structural discontinuities and basin geometry from gravity datasets (Cooper and Cowan, 2006; Verduzco et al., 2004). Nevertheless, conventional regional-residual separation techniques, such as polynomial fitting and wavelength filtering, frequently over-smooth anomaly fields and reduce the visibility of subtle geological structures, thereby limiting interpretation accuracy in structurally complex sedimentary basins.

The increasing availability of satellite-derived gravity data has significantly enhanced regional geophysical investigations. Modern global gravity field models, including GOCO06s, integrate observations from GOCE, GRACE, CHAMP, Swarm, satellite laser ranging, and terrestrial datasets to provide high-resolution representations of the Earth's gravity field suitable for lithospheric, tectonic, and sedimentary basin investigations (Kvas et al., 2021). Satellite gravity products have proven particularly valuable for regional structural mapping and petroleum exploration in areas where conventional ground gravity surveys remain sparse or unavailable.

Despite these advances, the application of deep learning techniques to satellite-derived gravity interpretation for petroleum prospectivity mapping remains relatively limited, particularly within African intracontinental sedimentary basins such as the Gongola Basin. Most previous investigations within the Upper Benue Trough have relied primarily on conventional gravity interpretation methods, spectral analysis, derivative enhancement, and manual geological interpretation (Fairhead and Okereke, 1987; Obaje et al., 2004; Obaje, 2009). The integration of deep learning architectures with satellite gravity datasets therefore offers an opportunity to improve structural interpretation, anomaly reconstruction, and automated petroleum prospectivity mapping while reducing interpretation subjectivity and computational complexity.

This study integrates satellite-derived GOCO06s gravity data with an attention-enhanced U-Net convolutional neural network for residual gravity anomaly reconstruction and petroleum reservoir prediction within the Gongola Basin, northeastern Nigeria. The proposed framework combines advanced deep learning techniques with gravity anomaly analysis to improve structural feature extraction, reservoir delineation, and regional petroleum prospectivity assessment, thereby providing a scalable and cost-effective approach for hydrocarbon exploration in frontier sedimentary basins.

2. MATERIALS AND METHODS

2.1. Geological Setting of the Study Area

The Gongola Basin is located within the Upper Benue Trough of northeastern Nigeria and extends across parts of Bauchi, Gombe, Adamawa, and Borno States and the basin constitutes one of the principal Cretaceous intracontinental rift basins of the West and Central African Rift System, which developed during the Early Cretaceous in response to extensional tectonics associated with the opening of the South Atlantic Ocean (Benkhelil, 1989; Genik, 1992). Subsequent tectonic reactivation and basin subsidence resulted in the formation of numerous fault-controlled depocenters, basement uplifts, and structural discontinuities that strongly influenced sediment accumulation and petroleum system evolution (Guiraud, 1990).

The sedimentary succession of the basin comprises the Bima Group, Yolde Formation, Pindiga Formation, Gombe Sandstone, and Kerri-Kerri Formation, which collectively consist of sandstone, shale, limestone, siltstone, and clay-rich sediments deposited under fluvial, deltaic, shallow marine, and continental environments (Zaborski et al., 1997; Obaje, 2009). The alternation of reservoir-quality sandstones with organic-rich shales and regional sealing units provides a favorable geological framework for hydrocarbon generation, migration, and accumulation within the basin (Obaje et al., 2004).

Structurally, the basin is characterized by extensive normal faulting, half-graben systems, basement highs, anticlinal structures, and fault-controlled sedimentary depressions trending predominantly in the NE–SW and NW–SE directions, reflecting the regional tectonic grain of the Upper Benue Trough (Fairhead and Okereke, 1987; Benkhelil, 1989). These structural elements controlled basin subsidence, sediment accommodation, and hydrocarbon migration pathways, leading to the development of several prospective structural and stratigraphic traps (Obaje, 2009).

Previous gravity, magnetic, and seismic investigations indicate that sedimentary thickness locally exceeds 4 km within the central part of the basin, providing sufficient burial conditions for source-rock maturation and hydrocarbon generation (Obaje et al., 2004;). The pronounced variations in basement depth and structural configuration produce significant lateral density contrasts that are expressed as gravity anomalies and can therefore be exploited to delineate basin architecture, fault systems, sedimentary depocenters, and potential hydrocarbon-bearing structures (Hinze et al., 2013; Lowrie and Fichtner, 2020). Consequently, the Gongola Basin provides an ideal geological setting for integrating satellite-derived gravity data with deep learning techniques to improve structural mapping and petroleum prospectivity assessment.

2.2. Gravity Data Acquisition

The study utilized satellite-derived gravity datasets obtained from the GOCO06s gravity field model. The GOCO06s model integrates observations from multiple satellite missions including GOCE, GRACE, CHAMP, Swarm, TerraSAR-X, and Satellite Laser Ranging systems. These datasets provide high-resolution representations of Earth’s gravity field suitable for regional and residual gravity anomaly analysis. Additional geological and structural datasets, including available seismic interpretations and published well information, were incorporated for training label generation and model validation.

2.3. Gravity Data Preprocessing

Standard gravity corrections were applied to the raw gravity datasets to improve anomaly accuracy, consistency, and reliability for subsurface interpretation. The preprocessing procedure involved the application of latitude correction to account for variations in the Earth’s rotational shape, free-air correction to compensate for elevation differences, Bouguer correction to remove the gravitational effects of subsurface rock masses, and terrain correction to minimize distortions caused by topographic irregularities. The datasets were subsequently reduced to a common datum to ensure uniformity and comparability across the study area.

The corrected gravity data were subsequently interpolated using minimum curvature gridding to generate continuous Bouguer anomaly maps. The processed gravity anomaly dataset revealed significant spatial variations across the study area, with gravity anomaly values ranging from approximately −10.90 mGal within the southern portions of the basin to about 10.95 mGal toward the northern sector. Negative gravity anomalies observed between longitudes 9.2345°E and 13.500°E and latitudes 8.288282°N to 8.736637°N indicate relatively low-density subsurface materials and thicker sedimentary accumulations, which are commonly associated with structurally depressed basin regions favorable for hydrocarbon generation and preservation. In contrast, positive gravity anomalies recorded between latitudes 10.33333°N and 11.56740°N suggest comparatively denser subsurface formations and possible uplifted basement structures.

The progressive transition from negative to positive gravity anomalies across the basin reflects significant lateral variations in subsurface density distribution and structural configuration. These variations provide important geophysical evidence for sedimentary thickness changes, basement undulations, fault-controlled structures, and possible hydrocarbon migration pathways within the Gongola Basin.

2.4. Regional-Residual Separation

Residual gravity anomalies were extracted through a two-stage filtering procedure. First, long-wavelength regional gravity trends were estimated using low-degree spherical harmonic representations derived from the GOCO06s model. Second, polynomial surface fitting and multi-scale median filtering techniques were applied to remove remaining broad regional effects. The resulting residual gravity anomaly maps emphasized short-wavelength structures associated with faults, structural highs, depocenters, and possible hydrocarbon traps.

2.5. Gravity Derivative Computation

2.5.1. Gravity derivative analysis

To improve the delineation of structural discontinuities and subsurface geological boundaries, several gravity derivative techniques were computed from the processed gravity anomaly datasets. These derivative methods enhanced the interpretation of faults, lithological contacts, basement configurations, and structural trends associated with petroleum accumulation within the Gongola Basin.

2.5.2. Vertical derivative

The vertical derivative technique was applied to enhance shallow subsurface structures and emphasize short-wavelength gravity anomalies associated with near-surface geological features. This method suppresses deeper regional signals while amplifying localized anomaly variations related to faults, fractures, and lithological boundaries (Telford et al., 1990). The first vertical derivative of the gravity field is mathematically expressed as:

$$\mathrm{VDR} = \frac{\partial g}{\partial z} \tag{1}$$

Where VDR represents derivatives, ∂g represents the gravity anomaly and ∂z denotes the vertical direction.

The application of the vertical derivative improved the visibility of shallow structural features and enhanced the delineation of tectonic discontinuities within the study area.

2.5.3. Horizontal gradient magnitude

The horizontal gradient magnitude was computed to identify lateral density contrasts and delineate the edges of subsurface geological structures. Maximum horizontal gradient values commonly occur along structural contacts and fault boundaries, making this method effective for structural mapping and basin boundary interpretation (Telford et al., 1990). The horizontal gradient magnitude is given by:

$$\mathrm{HGM} = \sqrt{\left(\left(\frac{\partial g}{\partial x}\right)^2 + \left(\frac{\partial g}{\partial y}\right)^2\right)} \tag{2}$$

This method significantly improved the identification of fault systems, basin margins, and structural lineaments within the Gongola Basin.

2.5.4. Analytic signal amplitude

The analytic signal amplitude was generated to improve anomaly localization independent of directional bias. The method combines both horizontal and vertical gravity derivatives to enhance the detection of subsurface source edges and structural geometries (Telford et al., 1990). The analytic signal amplitude is expressed as:

$$\mathrm{ASA} = \sqrt{\left(\left(\frac{\partial g}{\partial x}\right)^2 + \left(\frac{\partial g}{\partial y}\right)^2 + \left(\frac{\partial g}{\partial z}\right)^2\right)} \tag{3}$$

where the terms represent gravity gradients in the horizontal and vertical directions.

The analytic signal provided improved structural edge detection and enhanced the interpretation of fault-controlled subsurface features associated with petroleum accumulation.

2.5.5. Edge enhancement filtering

Edge enhancement filtering techniques were applied to sharpen gravity anomaly boundaries and improve the continuity of subtle structural features across the study area. These filters enhanced the visibility of fault trends, lithological contacts, and structural discontinuities that may not be easily identifiable from the original gravity anomaly data (Telford et al., 1990). One commonly applied edge enhancement operator is the tilt derivative, expressed as:

$$\text{Tilt} = \tan^{-1}\left(\frac{\frac{\partial g}{\partial z}}{\sqrt{\left(\left(\frac{\partial g}{\partial x}\right)^2 + \left(\frac{\partial g}{\partial y}\right)^2\right)}}\right) \tag{4}$$

This filtering approach improved the delineation of subtle structural edges and enhanced the interpretation of tectonic lineaments within the basin. The resulting gravity derivative products were subsequently integrated as multi-channel inputs into the convolutional neural network architecture, enabling the model to learn complementary structural, spatial, and textural characteristics associated with petroleum-related subsurface features.

2.6. Label Generation

Training labels for supervised learning were generated through the integration of:

i. Published geological and structural interpretations;
ii. Seismic and well-based structural information; and
iii. Expert interpretation of residual gravity anomaly signatures.

Ambiguous structural zones were excluded from supervised training to reduce classification uncertainty.

2.7. CNN Architecture and Model Development

2.7.1. Model architecture

An attention-enhanced U-Net architecture was developed for simultaneous gravity anomaly reconstruction and petroleum system feature classification. The model consisted of an encoder-decoder framework with skip connections to preserve multiscale spatial information (Ronneberger et al., 2015). The encoder section employed repeated convolution-batch normalization-ReLU blocks combined with strided convolutions for progressive feature extraction and dimensionality reduction (Goodfellow et al., 2016). Attention mechanisms were incorporated to improve feature weighting and emphasize geologically significant anomaly patterns by selectively enhancing informative features while suppressing irrelevant responses (Oktay et al., 2018; Vaswani et al., 2017). The decoder reconstructed spatial information through transposed convolution operations while integrating skip connections from corresponding encoder layers to recover fine-scale spatial details and improve localization accuracy (Ronneberger et al., 2015). The network included two output branches:

i. A regression head for continuous residual gravity reconstruction; and
ii. A classification head for petroleum system feature prediction, enabling simultaneous feature extraction and geological interpretation through multi-task learning (Caruana, 1997).

2.7.2. Loss functions

The regression task employed a combined Mean Squared Error (MSE) and Structural Similarity Index (SSIM) loss function to preserve both numerical accuracy and spatial texture during gravity anomaly reconstruction (Wang et al., 2004). For classification, categorical cross-entropy combined with focal loss was implemented to address class imbalance and improve sensitivity to underrepresented petroleum system features (Lin et al., 2017). The total loss function was expressed as a weighted combination of regression and classification losses to jointly optimize anomaly reconstruction and petroleum feature classification during network training.

2.8. Training Procedure

The convolutional neural network was trained using gravity anomaly tiles measuring 128 × 128 km, which were subsequently resampled into 128 × 128-pixel grids to ensure computational efficiency and spatial consistency during model training. To improve model generalization and robustness against spatial variability, data augmentation techniques including random rotations, horizontal and vertical flipping, and Gaussian noise injection were applied throughout the training process (Shorten and Khoshgoftaar, 2019). These augmentation strategies enabled the network to learn invariant geological features while reducing sensitivity to orientation-dependent gravity anomaly patterns. Model optimization was performed using the Adam optimizer, which adaptively estimates first- and second-order moments of the gradients to improve convergence efficiency and training stability for deep neural networks (Kingma and Ba, 2015).

To ensure robust model evaluation, the dataset was partitioned into 70% training, 15% validation, and 15% testing subsets using spatially independent sampling. The spatial separation of validation samples minimized data leakage and ensured that model performance was assessed on previously unseen geological regions, thereby improving the reliability and generalization capability of the predictive framework (Bergen et al., 2019).

The integrated geological and geophysical information was converted into raster-based label masks corresponding to four petroleum system feature classes, namely faults, structural highs, depocenters, and stratigraphic traps, together with background non-prospective areas. Label generation was performed through manual digitization by integrating published geological maps, interpreted seismic structures, well-control information, and residual gravity anomaly signatures within a geographic information system (GIS) environment. The resulting labeled dataset was subsequently reviewed for spatial consistency and used to train, validate, and test the convolutional neural network under supervised learning conditions.

3. RESULTS AND DISCUSSION

3.1. Residual Gravity Anomaly Reconstruction

The CNN-Predicted Petroleum Reservoir Zones map of the Gongola Basin, Nigeria was presented in Figure 1 below. The CNN-predicted petroleum reservoir zones map of the Gongola Basin illustrates the spatial distribution of petroleum reservoir probability derived from residual satellite gravity anomalies (GOCO06s). The trained CNN model successfully identified gravity patterns associated with potential hydrocarbon accumulations. Prediction confidence ranges from -2.0 (low probability) to +2.0 (high probability), with warmer colors indicating areas of higher reservoir prospectivity. The map also highlights interpreted structural and stratigraphic trapping features using cyan polygons, while black lines delineate directional trends and basin boundaries.

The CNN-derived petroleum reservoir probability map indicates that the highest reservoir prospectivity is concentrated within the central and southwestern sectors of the Gongola Basin, where broad residual gravity lows coincide with structurally enclosed anomaly patterns. Such gravity lows are generally interpreted as thick accumulations of low-density sedimentary rocks overlying the crystalline basement and are commonly associated with favorable conditions for hydrocarbon generation and preservation because of increased burial depth and thermal maturation of source rocks (Hinze et al., 2013). The observed spatial distribution therefore suggests that these sectors constitute the principal sedimentary depocenters of the basin and represent the most prospective zones for petroleum accumulation (Telford et al., 1990)

The elongated anomaly belts trending predominantly in the NE–SW and NW–SE directions reflect the major tectonic grain of the Upper Benue Trough. These structural orientations originated during Early Cretaceous continental rifting and were subsequently modified by Santonian tectonic compression and later reactivation events, producing numerous normal faults, transfer faults, and fracture systems that controlled basin subsidence and sediment distribution (Benkhelil, 1989; Guiraud, 1990). The coincidence between the CNN-derived structural trends and the known tectonic framework indicates that the deep learning model successfully preserved regional structural information embedded within the gravity field. Since basement faults commonly serve as migration pathways for hydrocarbons and influence structural trap formation, their identification provides important evidence for petroleum prospectivity within the basin (Obaje, 2009).

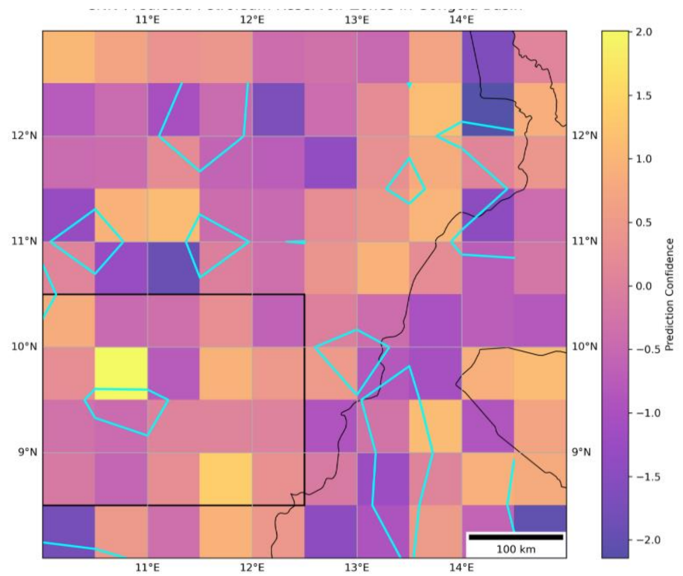

Figure 1: CNN-predicted petroleum reservoir zones in the Gongola Basin

3.2. Structural Interpretation of Gravity Gradient Variations

The contour map of petroleum reservoir probability (Figure 2) presented the spatial distribution of CNN-predicted petroleum prospectivity across the Gongola Basin. Probability values ranged from near 0.0 in the western and eastern extremities to above 0.9 in the central part of the basin. The highest probability zones (> 0.8) are concentrated between latitudes 8.9° N and 9.4° N, and longitudes 10.6° E and 11.3° E. These areas corresponded to structurally favorable regions where previous gravity anomaly studies have identified subsurface closures and thick sedimentary packages conducive to Petroleum accumulation (Hinze et al., 2013).

The closely spaced contour intervals observed within the central basin indicate steep gravity gradients associated with abrupt density contrasts across basement faults and structural discontinuities (Telford et al., 1990). Such gradients commonly mark fault-controlled basin margins, horst-graben systems, or basement uplifts that compartmentalize sedimentary sequences and create favorable structural traps for hydrocarbon accumulation (Blakely, 1995; Telford et al., 1990). In contrast, the gently spaced contours identified toward the eastern part of the basin suggest gradual basement relief and relatively uniform sedimentary deposition, implying lower structural complexity and reduced trapping efficiency. This relationship between gravity gradients and subsurface structural configuration has been widely documented in gravity investigations of sedimentary basins worldwide (Hinze et al., 2013).

The structural closures delineated in the southwestern sector constitute another significant feature identified by the CNN model. Structural closures are among the most effective trapping mechanisms for hydrocarbons because they provide enclosed geometries capable of retaining migrated petroleum beneath impermeable sealing formations (Magoon and Dow, 1994). Their occurrence within regions of pronounced gravity lows suggests that these structures are associated with relatively deep sedimentary depocenters that may have experienced prolonged subsidence and enhanced hydrocarbon maturation. Consequently, these areas should be regarded as priority targets for detailed seismic surveys and exploratory drilling.

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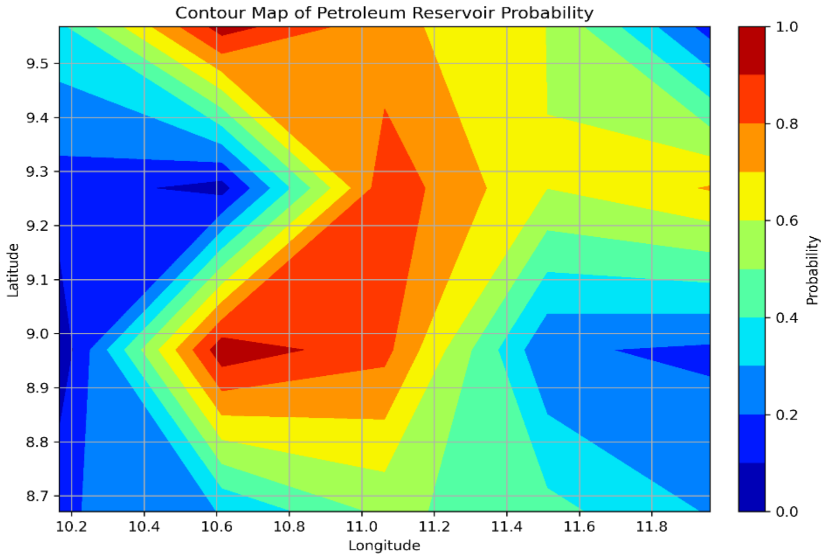

Figure 2: Contour map of petroleum reservoir probability of the Gongola Basin

3.3. Petroleum Reservoir Zonation

The petroleum reservoir zonation map (Figure 3) classifies the Gongola Basin into high-, moderate-, and low-petroleum prospectivity zones based on the integration of residual gravity anomaly interpretation and CNN-derived reservoir prediction outputs. The spatial distribution reflects variations in subsurface density contrasts, structural architecture, and sedimentary basin geometry that influence hydrocarbon generation, migration, trapping, and preservation. The high-prospectivity zones are concentrated mainly within the central and southwestern parts of the basin, where pronounced residual gravity lows coincide with structurally enclosed anomaly patterns and major fault intersections. These gravity lows are interpreted as deep sedimentary depocenters filled with relatively low-density sediments overlying denser crystalline basement rocks, providing favorable conditions for source rock maturation and hydrocarbon accumulation (Telford et al., 1990). The association of gravity lows with structural closures further indicates the presence of fault-controlled traps that enhance hydrocarbon migration and preservation.

Moderate-prospectivity zones occur around the principal depocenters and exhibit intermediate residual gravity amplitudes, reflecting moderate sedimentary thickness and less pronounced structural deformation (Genik, 1992). These areas may contain smaller structural or stratigraphic traps and therefore remain important secondary exploration targets. In contrast, low-prospectivity zones are mainly distributed along uplifted basin margins where relatively high gravity values indicate shallow basement conditions and limited sedimentary cover, reducing the likelihood of hydrocarbon generation and trapping (Genik, 1992; Obaje et al., 2004).

The observed zonation pattern reflects the tectonic evolution of the Gongola Basin within the Upper Benue Trough, where syn-rift extension produced fault-controlled depocenters and horst-graben structures that governed sediment accumulation and petroleum system development (Fairhead and Okereke, 1987). Similar relationships between gravity anomalies, sediment thickness, and hydrocarbon prospectivity have been reported in intracontinental rift basins using gravity-derived structural mapping techniques (Blakely, 1995; Fairhead and Okereke, 1987). The CNN model successfully captures these complex spatial relationships by integrating multiscale gravity signatures that are difficult to identify using conventional interpretation methods.

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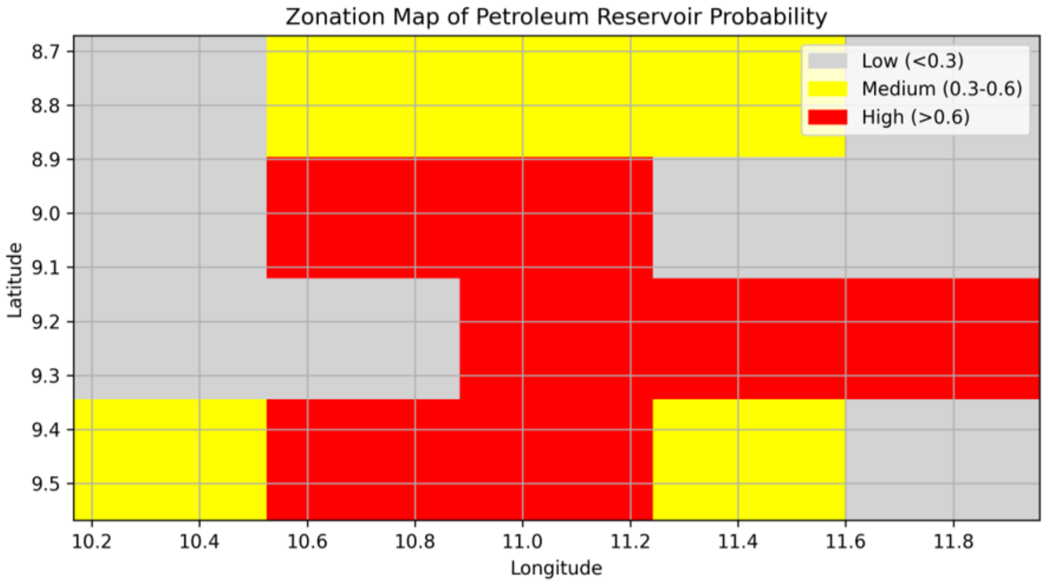

Figure 3: Zonation map of petroleum reservoir of the Gongola Basin

The resulting petroleum prospectivity pattern is consistent with previous geological and geophysical investigations that identified the central Gongola Basin and adjoining structural depressions as the most favorable regions for hydrocarbon exploration because of their greater sediment thickness and favorable tectono-stratigraphic evolution (Obaje et al., 2004; Zaborski et al., 1997). Overall, the integration of satellite-derived gravity data with CNN-based interpretation provides a reliable regional petroleum reservoir zonation framework capable of supporting future seismic acquisition, exploratory drilling, and petroleum exploration planning while reducing exploration uncertainty through improved structural characterization.

3.4. Uncertainty Assessment

Monte Carlo dropout was implemented during inference to evaluate model uncertainty and confidence reliability (Figure 4). The uncertainty map indicates relatively low uncertainty within the central Gongola Basin, where gravity anomaly signatures are structurally coherent and adequately represented in the training dataset, suggesting high prediction confidence. In contrast, elevated uncertainty occurs along the basin margins and structurally complex zones, where abrupt gravity gradients and heterogeneous basement structures increase geological ambiguity. Similar uncertainty patterns have been reported in deep learning-based geophysical inversion studies, where prediction confidence decreases in regions characterized by complex structural variations (Gal and Ghahramani, 2016; Goodfellow et al., 2016).

The uncertainty histogram further shows that most predictions exhibit low uncertainty levels, confirming the robustness and generalization capability of the attention-enhanced CNN framework across much of the study area. The correspondence between low uncertainty and structurally coherent sedimentary depocenters demonstrates that the model effectively captured the relationship between gravity anomalies and petroleum-bearing structures, while areas of higher uncertainty identify zones that may require additional seismic or well-log constraints for improved characterization (LeCun et al., 2015).

Overall, the uncertainty assessment validates the reliability of the generated petroleum prospectivity map and highlights the value of uncertainty quantification for reducing exploration risk and prioritizing future geophysical investigations within the Gongola Basin (Obaje et al., 2004; Zaborski et al., 1997).

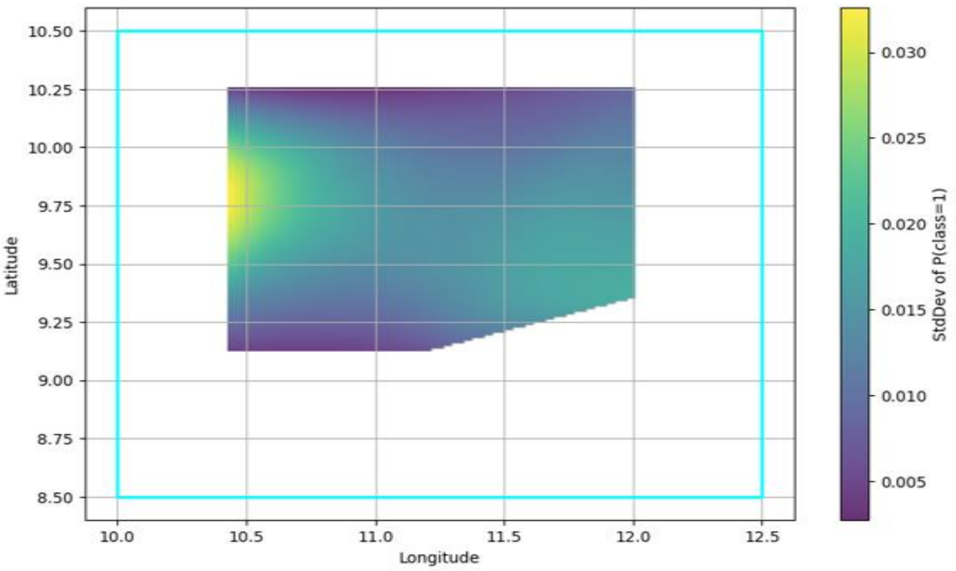

Figure 4: Uncertainty heat map of the Gongola Basin

4. CONCLUSION

This study developed an attention-enhanced convolutional neural network framework for residual gravity anomaly reconstruction and petroleum system feature identification within the Gongola Basin, northeastern Nigeria. Satellite-derived gravity data obtained from the GOCO06s gravity field model were processed to isolate residual anomalies associated with petroleum-related structures. The proposed CNN architecture successfully reconstructed gravity anomaly fields and classified structural features including faults, structural highs, basin lows, and stratigraphic traps. Monte Carlo dropout uncertainty analysis demonstrated that the model produced stable and reliable predictions across most portions of the study area while highlighting structurally ambiguous regions requiring additional investigation.

Based on the findings of this study, the integration of deep learning techniques with gravity anomaly interpretation should be further expanded for petroleum exploration within frontier sedimentary basins. The application of convolutional neural networks demonstrated significant potential for improving reservoir characterization, structural mapping, and petroleum prospectivity assessment within the Gongola Basin. Consequently, future exploration programs within the basin should incorporate artificial intelligence-driven geophysical interpretation frameworks to enhance exploration efficiency and reduce interpretation uncertainty.

The study further recommends the integration of additional geophysical datasets such as seismic reflection data, magnetic anomaly data, well-log information, and electromagnetic surveys into the deep learning framework. The incorporation of multi-source geophysical information would improve subsurface characterization accuracy and enhance the reliability of hydrocarbon prospectivity prediction.

Overall, the integration of satellite-derived gravity data and deep learning techniques provides a rapid, scalable, and cost-effective framework for petroleum exploration in frontier sedimentary basins. Future studies should focus on integrating multi-geophysical datasets and advanced uncertainty-aware deep learning architectures to further improve exploration reliability and geological interpretability.

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6. CONFLICT OF INTEREST

There is no conflict of interest associated with this work.

REFERENCES

Arigbe, O. D., Oyeneyin, M. B., Arana, I., and Ghazi, M. D. (2019). Real-time relative permeability prediction using deep learning. *Journal of Petroleum Exploration and Production Technology,* **9**(2), 1271–1284. https://doi.org/10.1007/s13202-018-0578-5

Benkhelil, J. (1989). The origin and evolution of the Cretaceous Benue Trough (Nigeria). *Journal of African Earth Sciences, 8*(2–4), 251–282. https://doi.org/10.1016/S0899-5362(89)80028-4

Bergen, K. J., Johnson, P. A., de Hoop, M. V., and Beroza, G. C. (2019). Machine learning for data-driven discovery in solid Earth geoscience. *Science, 363*(6433), eaau0323. https://doi.org/10.1126/science.aau0323

Blakely, R. J. (1995). *Potential theory in gravity and magnetic applications. Cambridge University Press*.

Caruana, R. (1997). *Multitask learning*. Machine Learning, 28(1), 41–75.

Cooper, G. R. J., and Cowan, D. R. (2006). Enhancing potential field data using filters based on the local phase. *Computers and Geosciences, 32*(10), 1585–1591. https://doi.org/10.1016/j.cageo.2006.02.016.

Fairhead, J. D., and Okereke, C. S. (1987). A regional gravity study of the West African rift system in Nigeria and Cameroon and its tectonic interpretation. *Tectonophysics, 143*(1–3), 141–159.

Gal, Y., and Ghahramani, Z. (2016). Dropout as a Bayesian approximation: Representing model uncertainty in deep learning. *Proceedings of the 33rd International Conference on Machine Learning*, 1050–1059.

Genik, G. J. (1992). Regional framework, structural and petroleum aspects of rift basins in Niger, Chad and Central African Republic (CAR). *Tectonophysics, 213*(1–2), 169–185.

Goodfellow, I., Bengio, Y., and Courville, A. (2016). Deep feedforward networks. *Deep learning*. MIT Press.

Guiraud, R. (1990). Tectono-sedimentary framework of the Early Cretaceous continental Bima Formation (Upper Benue Trough, Nigeria). *Journal of African Earth Sciences, 10*(1–2), 341–353.

Hinze, W. J., von Frese, R. R. B., and Saad, A. H. (2013). *Gravity and magnetic exploration: Principles, practices, and applications*. Cambridge University Press.

Kingma, D. P., and Ba, J. (2015). *Adam: A method for stochastic optimization*. In *Proceedings of the 3rd International Conference on Learning Representations (ICLR)*.

Kvas, A., Mayer-Gürr, T., Krauss, S., Brockmann, J. M., Schubert, T., Schuh, W.-D., Pail, R., Gruber, T., Jäggi, A., and Meyer, U. (2021). The satellite-only gravity field model GOCO06s. *Journal of Geodesy, 95*, Article 49. https://doi.org/10.1007/s00190-021-01497-8

LeCun, Y., Bengio, Y., and Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436–444. https://doi.org/10.1038/nature14539

Li, H., Chen, S., Li, Y., Zhang, B., Zhao, M., and Han, J. (2023). Stable downward continuation of the gravity potential field implemented using deep learning. *Frontiers in Earth Science, 10*, 1065252. https://doi.org/10.3389/feart.2022.1065252

Lin, T.-Y., Goyal, P., Girshick, R., He, K., and Dollár, P. (2017). *Focal loss for dense object detection*. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)* (pp. 2980–2988).

Lowrie, W., and Fichtner, A. (2020). *Fundamentals of geophysics* (3rd ed.). Cambridge University Press.

Obaje, N. G. (2009). *Geology and mineral resources of Nigeria*. Springer.

Obaje, N. G., Attah, D. O., Opeloye, S. A., and Moumouni, A. (2004). Geochemical evaluation of the hydrocarbon prospects of sedimentary basins in Nigeria. *NAPE Bulletin, 17*, 1–12.

Oktay, O., Schlemper, J., Le Folgoc, L., Lee, M., Heinrich, M., Misawa, K., Mori, K., McDonagh, S., Hammerla, N. Y., Kainz, B., Glocker, B., and Rueckert, D. (2018). *Attention U-Net: Learning where to look for the pancreas*. *arXiv preprint arXiv:1804.03999*.

Ronneberger, O., Fischer, P., and Brox, T. (2015). U-Net: Convolutional networks for biomedical image segmentation. In *Proceedings of the 18th International Conference on Medical Image Computing and Computer-Assisted Intervention (MICCAI 2015)* (pp. 234–241). Springer. https://doi.org/10.1007/978-3-319-24574-4_28

Shorten, C., and Khoshgoftaar, T. M. (2019). A survey on image data augmentation for deep learning. *Journal of Big Data*, 6, 60. https://doi.org/10.1186/s40537-019-0197-0

Telford, W. M., Geldart, L. P., and Sheriff, R. E. (1990). *Applied geophysics* (2nd ed.). Cambridge University Press.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., and Polosukhin, I. (2017). *Attention is all you need*. In *Advances in Neural Information Processing Systems, 30*.

Verduzco, B., Fairhead, J. D., Green, C. M., and MacKenzie, C. (2004). New insights into magnetic derivatives for structural mapping. *The Leading Edge, 23*(2), 116–119.

Wang, Z., Bovik, A. C., Sheikh, H. R., and Simoncelli, E. P. (2004). Image quality assessment: From error visibility to structural similarity. *IEEE Transactions on Image Processing*, 13(4), 600–612.

Zaborski, P., Ugodulunwa, F., Idornigie, A., Nnabo, P., and Ibe, K. (1997). Stratigraphy and structure of the Cretaceous Gongola Basin, northeastern Nigeria. *Bulletin des Centres de Recherches Exploration-Production Elf Aquitaine, 21*(1), 153–185.

Zhang, T., Tilke, P., Dupont, E., Zhu, L., Liang, L., & Bailey, W. (2019). Generating geologically realistic 3D reservoir facies models using deep learning of sedimentary architecture with generative adversarial networks. In: *International Petroleum Technology Conference* (p. D031S067R001). IPTC.