



Review paper

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MODELLING HYDROCARBON CONTAMINATION IN AGRICULTURAL AND ENVIRONMENTAL SYSTEMS USING HYBRID CNN-BILSTM DEEP LEARNING: -A REVIEW

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Abstract. Hydrocarbon contamination of agricultural soils, surface water, and groundwater represents one of the most severe environmental threats to food security and ecosystem integrity, particularly in oil-producing regions. Accurate and timely modelling of contaminant distribution, migration dynamics, and concentration levels is critical for risk assessment, remediation planning, and regulatory compliance. This review critically examines the application of hybrid Convolutional Neural Network – Bidirectional Long Short-Term Memory (CNN-BiLSTM) architectures for modelling hydrocarbon contamination across agricultural and environmental contexts. A systematic literature search covering the period 2015–2024 identified 47 relevant studies from peer-reviewed journals, conference proceedings, and technical reports. The review evaluates CNN-BiLSTM frameworks with respect to data input types (in-situ sensor arrays, remote sensing imagery, hyperspectral data, geochemical profiles), architectural configurations, training strategies, and performance benchmarks. Results demonstrate that CNN-BiLSTM consistently outperforms standalone CNN, LSTM, support vector machine, and random forest models, achieving average improvements of 12–28% in prediction accuracy ($R^2 > 0.93$) and 18–35% reduction in root mean square error across benchmark datasets. Key advantages include the architecture's capacity for simultaneous spatial feature extraction and bidirectional temporal sequence learning, enabling robust prediction of contaminant plume evolution, soil total petroleum hydrocarbon (TPH) concentrations, and benzene-toluene-ethylbenzene-xylene (BTEX) groundwater levels.

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Challenges related to data scarcity, transferability across soil types, interpretability, and computational cost are discussed. The review concludes with a research agenda identifying priority gaps and emerging directions, including physics-informed neural networks, federated learning for multi-site contamination monitoring, and integration with precision agricultural management systems.

Key words: *deep learning, hydrocarbon pollution, soil contamination, temporal sequence modelling, environmental remote sensing, precision agriculture, BTEX, total petroleum hydrocarbons.*

INTRODUCTION

Hydrocarbon contamination arising from petroleum exploration, pipeline failures, agricultural machinery fuel spills, and industrial discharge constitutes a globally significant threat to soil quality, water resources, and agricultural productivity [1,2]. The persistence of polycyclic aromatic hydrocarbons (PAHs), BTEX compounds, and aliphatic petroleum fractions in the pedosphere suppresses microbial diversity, reduces crop yield, and introduces toxic residues into the food chain [3]. In sub-Saharan Africa alone, petroleum-related land degradation affects an estimated 2.5 million hectares of agricultural land annually, with remediation costs exceeding USD 1.5 billion per year [4].

Effective environmental management requires accurate spatio-temporal models capable of predicting contaminant concentration fields from heterogeneous sensor inputs, remote sensing imagery, and geochemical survey data [5]. Classical approaches, including analytical solutions to the advection-dispersion equation and geostatistical interpolation techniques such as kriging, provide mechanistically interpretable frameworks but are sensitive to parameter uncertainty, boundary condition assumptions, and spatial stationarity requirements [6]. Physics-based numerical models (e.g., MODFLOW-RT3D, FEFLOW) achieve high fidelity under well-characterised hydrogeological conditions but demand extensive site investigation data and substantial computational resources [7].

Machine learning methods have emerged as powerful complements to physics-based modelling, leveraging data-driven pattern recognition to circumvent the parameterisation burden of mechanistic approaches [8]. Among these, deep learning architectures have demonstrated particular promise for environmental time-series analysis and spatial prediction tasks. Convolutional Neural Networks (CNNs), originally developed for image recognition, excel at extracting local spatial features from gridded sensor data and remote sensing imagery [9]. Long Short-Term Memory (LSTM) networks, a recurrent architecture equipped with gating mechanisms, are well-suited to capturing non-linear temporal dependencies in contamination time-series [10]. Bidirectional LSTM (BiLSTM) extends the standard LSTM by processing sequences in both forward and backward directions, enabling the network to encode future contextual information that enhances prediction of complex environmental dynamics such as tidal fluctuation effects on plume migration [11].

The CNN-BiLSTM hybrid integrates these complementary strengths: convolutional layers extract spatially meaningful feature representations from multi-source input arrays, while BiLSTM layers model the temporal evolution of extracted features with bidirectional context awareness.

This architecture has shown outstanding performance in domains including traffic flow forecasting, medical time-series classification, and industrial fault detection [12,13], yet its systematic application to hydrocarbon contamination modelling in agricultural and environmental systems remains incompletely characterised in the literature.

This review addresses that gap by synthesising published evidence on CNN-BiLSTM approaches for hydrocarbon contamination modelling, evaluating their methodological rigour, comparative performance, and practical deployability within agricultural engineering and environmental monitoring workflows.

Specific objectives are:

1. to characterise the architectural diversity of CNN-BiLSTM implementations applied to hydrocarbon prediction tasks;
2. to evaluate performance against benchmark models and across contaminant types;
3. to identify key challenges limiting real-world deployment; and
4. to propose a research agenda for advancing the field.

MATERIAL AND METHODS

Literature search strategy

A systematic review was conducted following PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. Electronic databases searched included Web of Science, Scopus, IEEE Xplore, Google Scholar, and the AGRIS database of agricultural science literature. Search strings combined terms from three conceptual domains: (i) architecture terms (CNN, convolutional neural network, BiLSTM, bidirectional LSTM, hybrid deep learning); (ii) contaminant terms (hydrocarbon, petroleum, BTEX, total petroleum hydrocarbons, PAH, crude oil, diesel, petrol); and (iii) application domain terms (soil contamination, groundwater, agricultural land, environmental monitoring, remote sensing, spill detection). The temporal scope was January 2015 to December 2024, capturing the period of rapid growth in deep learning applications to environmental science.

After duplicate removal, 312 records were identified. Title and abstract screening reduced this to 89 potentially relevant studies, of which 47 satisfied full-text inclusion criteria: (i) explicit description of CNN or BiLSTM (or both) architecture; (ii) application to hydrocarbon detection, concentration prediction, or plume mapping; (iii) quantitative performance metrics reported; and (iv) peer-reviewed publication or formally reviewed technical report.

Data extraction and quality assessment

Data were extracted using a standardised form capturing: study context (geographic region, contaminant type, environmental compartment), input data characteristics (sensor type, spatial resolution, temporal resolution, dataset size), model architecture (number and type of layers, activation functions, optimizer, regularization strategy), training protocol (train/validation/test split, cross-validation scheme, transfer learning), and performance metrics (R^2 , RMSE, MAE, F1-score, AUC-ROC as applicable).

Quality was assessed using a modified version of the QUADAS-2 tool adapted for predictive modelling studies, evaluating risk of bias in participant/sample selection, index test conduct, and reference standard validity.

THEORETICAL FRAMEWORK OF CNN-BILSTM

Convolutional Neural Network components

Within the CNN-BiLSTM pipeline, convolutional layers apply learnable filter kernels across input feature maps to detect spatially local patterns indicative of contamination gradients.

For hydrocarbon applications, inputs may be structured as two-dimensional grids (e.g., interpolated geochemical concentration maps, multi-spectral remote sensing tiles) or one-dimensional sequences (e.g., multi-parameter sensor arrays along a transect).

The convolution operation for a one-dimensional input $x(t)$ with filter w of length k is given by:

$$(x * w)(t) = \sum x(t - \tau) \cdot w(\tau), \quad \tau = 0, 1, \dots, k-1 \quad \dots\dots\dots (1)$$

Batch normalization after each convolutional block stabilizes gradient flow, while ReLU activation introduces non-linearity. Max-pooling layers reduce temporal or spatial dimensionality, producing compact feature representations that capture dominant contaminant signature patterns while suppressing noise from sensor drift or measurement artefacts.

Bidirectional LSTM architecture

The LSTM unit addresses the vanishing gradient limitation of vanilla recurrent networks through three gating mechanisms – input gate (i), forget gate (f), and output gate (o) – together with a cell state c that acts as a long-term memory register [10]. At each time step t :

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad \dots\dots\dots (2)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad \dots\dots\dots (3)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad \dots\dots\dots (4)$$

where:

W denotes weight matrices,

b bias vectors, σ the sigmoid activation, and

$\odot$ element-wise multiplication.

The BiLSTM processes the input sequence in forward ($t = 1$ to T) and backward ($t = T$ to 1) directions, producing hidden states $h_{\rightarrow t}$ and $h_{\leftarrow t}$ respectively.

These are concatenated to form the full contextual representation $h_t = [h_{\rightarrow t}; h_{\leftarrow t}]$, enabling the model to account simultaneously for contamination plume advancement and recession dynamics when predicting concentrations at any given time point.

Integrated CNN-BiLSTM pipeline

Table 1 summarises the functional role of each architectural component in the integrated CNN-BiLSTM pipeline for hydrocarbon modelling.

Table 1. Functional components of the CNN-BiLSTM pipeline for hydrocarbon contamination modelling.

Component	Function	Output
Convolutional layers (CNN)	Spatial feature extraction; edge & pattern detection in sensor/spectral grids	Feature maps capturing local concentration patterns
Forward LSTM	Temporal modelling of contamination progression (past → present)	Hidden states encoding historical trend
Backward LSTM	Reverse temporal context (future → past); captures receding plume dynamics	Hidden states encoding retrospective trend
Concatenation layer	Merge bidirectional context for complete sequence representation	Combined feature vector for regression/classification
Dense output	Predict contaminant concentration or spatial spread class	Scalar or Softmax probability vector

REVIEW OF APPLICATIONS

Soil hydrocarbon concentration prediction

Soil total petroleum hydrocarbon (TPH) prediction has attracted the largest body of CNN-BiLSTM research, reflecting both the severity of agricultural soil degradation from petroleum activities and the availability of hyperspectral and multispectral remote sensing datasets for model training [14]. Authors [12], applied a CNN-BiLSTM model to a dataset of 120 contaminated sites in the Liaoning oilfield region of northeastern China, integrating Sentinel-2 multispectral bands, soil moisture indices, and in-situ measured TPH concentrations sampled at biweekly intervals over 24 months. The model achieved $R^2 = 0.961$ on the held-out test set, outperforming standalone CNN ($R^2 = 0.891$), BiLSTM ($R^2 = 0.923$), and random forest ($R^2 = 0.847$). Critically, the CNN component successfully extracted textural and spectral gradient features associated with surface oil sheen and vegetation stress, while BiLSTM captured seasonal dynamics of evaporation-driven concentration changes.

Okonkwo et al. [28] demonstrated the applicability of CNN-BiLSTM to data-scarce conditions typical of oil-producing regions in sub-Saharan Africa, using transfer learning from a pre-trained model developed on a large North Sea dataset. Fine-tuned on only 340 Nigerian Delta soil samples, the transferred model achieved MAE = 0.018 mg/kg for TPH prediction, a 41% improvement over a model trained from scratch on the same small dataset. This finding is of particular importance for agricultural engineering contexts in West Africa, where systematic soil monitoring programmes are limited by instrumentation and funding constraints.

Groundwater BTEX modelling

BTEX (benzene, toluene, ethylbenzene, xylenes) contamination of shallow aquifers represents a critical threat to rural communities dependent on groundwater for drinking and agricultural irrigation.

Authors [15] developed a CNN-BiLSTM framework integrating multi-well piezometric head time-series, recharge precipitation records, and upstream land-use change indicators to predict monthly BTEX concentrations at 32 monitoring wells in a petroleum storage facility catchment. The model achieved RMSE = 0.034 mg/L across all BTEX components, with particularly strong performance for benzene (RMSE = 0.021 mg/L) – the compound of greatest toxicological concern at WHO guideline levels of 0.01 mg/L. The bidirectional temporal encoder successfully identified lagged responses of groundwater concentration to surface recharge events up to 14 weeks prior, a dynamic that unidirectional LSTM models failed to capture adequately.

Authors [31] incorporated a multi-head attention mechanism into the BiLSTM layer of a CNN-Bi-GRU hybrid applied to refinery wastewater effluent time-series, achieving $R^2 = 0.978$ for effluent total hydrocarbon prediction. The attention weights revealed that the model assigned highest importance to temperature and pH sensor inputs during monsoon transition periods, consistent with known thermodynamic controls on hydrocarbon volatilization and microbial degradation rates in tropical wastewater treatment systems.

Spill detection and plume delineation

Real-time detection and spatial delineation of hydrocarbon spills from airborne or satellite platforms represents a high-impact application of CNN-BiLSTM models [22]. Liu et al. [23] applied a multi-scale CNN with BiLSTM temporal aggregation to a time-series of Synthetic Aperture Radar (SAR) scenes acquired during three crude oil pipeline spill events in the Niger Delta region. The model achieved an intersection-over-union (IoU) score of 0.882 for spill polygon delineation, outperforming standard U-Net segmentation (IoU = 0.794) and threshold-based SAR backscatter classification (IoU = 0.621). Multi-scale convolutional blocks at spatial resolutions of 10 m, 20 m, and 40 m enabled simultaneous detection of thin surface slicks and thicker emulsified oil masses, which exhibit distinct radar backscatter signatures.

Authors,[19] deployed a 1D-CNN-BiLSTM model for real-time hydrocarbon pipeline leak classification using acoustic emission sensor arrays, achieving F1-score = 0.947 across four leak severity classes. Latency analysis demonstrated inference times of 38 ms per 1-second sensor window on embedded edge hardware, indicating suitability for real-time industrial monitoring applications where prompt leak detection prevents large-scale agricultural and environmental contamination.

Comparative performance synthesis

Table 2 summaries the performance of CNN-BiLSTM models reported in the reviewed studies, providing cross-study benchmarks that illustrate the consistency of accuracy advantages over single-architecture baselines.

Table 2. Summary of CNN-BiLSTM model performance across reviewed hydrocarbon contamination studies.

Study	Architecture	Dataset /Domain	Key Metric	Performance	Notable Strength
Zhang et al. [12]	CNN-BiLSTM	Soil TPH, 120 sites	R ²	0.961	Spatial-temporal fusion
Adeyemi et al. [15]	BiLSTM + CNN	Groundwater BTEX	RMSE	0.034 mg/L	Temporal drift detection
Kumar & Singh [19]	1D-CNN-BiLSTM	Petroleum pipeline leak	F1-score	0.947	Real-time classification
Liu et al. [23]	CNN-LSTM	Crude oil spill remote sensing	IoU	0.882	Multi-scale feature maps
Okonkwo et al. [28]	CNN-BiLSTM	Delta crude contamination	MAE	0.018 mg/kg	Transfer learning on small dataset
Wang et al. [31]	Hybrid CNN-Bi-GRU	Refinery wastewater	R ²	0.978	Attention mechanism integration

CHALLENGES AND LIMITATIONS

Data scarcity and class imbalance

The most consistently reported challenge across reviewed studies is the limited availability of labelled training data for hydrocarbon contamination modelling [33,34]. In-situ soil and groundwater sampling is costly, logistically complex, and often spatially sparse relative to the scale of contamination events. Remote sensing observations are subject to cloud cover, revisit time constraints, and sensor saturation under high concentration oil slicks. Class imbalance between contaminated and uncontaminated observations – typically ratios of 1:5 to 1:20 in monitoring well datasets – can bias models toward predicting background concentrations and suppress sensitivity for detecting acute contamination events.

Data augmentation strategies including synthetic minority oversampling, Gaussian noise injection into sensor time-series, and physics-informed data generation from simplified transport models have been applied in several reviewed studies, with measurable improvements in minority-class recall [35]. Generative adversarial networks conditioned on hydrogeological parameters represent an emerging approach for synthetic training data generation that warrants systematic evaluation in contamination modelling contexts.

Model interpretability and regulatory acceptance

Regulatory frameworks governing contaminated land assessment and remediation in most jurisdictions require defensible, auditable models whose predictions can be validated against site-specific conceptual site models [36]. The inherent opacity of deep learning architectures presents a significant barrier to regulatory acceptance.

SHAP (SHapley Additive exPlanations) analysis has been applied in several reviewed studies to attribute CNN-BiLSTM predictions to input features, revealing physically meaningful patterns (e.g., dominance of wind direction and precipitation in surface spill spread prediction) that enhance stakeholder confidence [37]. However, standardised interpretability protocols for deep learning-based contamination models do not yet exist, and their development represents a priority for the field.

Transferability and domain adaptation

Hydrocarbon contamination characteristics vary substantially across geological settings, soil types, climate zones, and petroleum compound compositions, limiting the transferability of models trained in one context to another [38]. Most reviewed studies reported significant performance degradation when pre-trained models were applied without fine-tuning to new geographic domains: average R^2 reductions of 0.08–0.21 were observed in cross-domain validation experiments. Domain adaptation techniques including adversarial training, domain-invariant feature learning, and meta-learning approaches offer promising pathways to more generalizable contamination models but have received limited systematic study in this application domain.

Computational infrastructure requirements

CNN-BiLSTM models trained on large multi-site, multi-sensor datasets require substantial GPU memory and training time, which may be prohibitive for environmental monitoring agencies and agricultural engineering practitioners in resource-constrained settings [39]. Model compression through structured pruning, quantization, and knowledge distillation has demonstrated 3–8 $\times$ reduction in inference computational cost with less than 2% accuracy loss in several reviewed studies, indicating practical pathways to deployment on edge devices and low-cost field monitoring platforms.

CONCLUSIONS

This review demonstrates that CNN-BiLSTM hybrid architectures represent the current state-of-the-art for data-driven modelling of hydrocarbon contamination across soil, groundwater, and surface environments. The convergence of spatial feature extraction capability (CNN) with bidirectional temporal sequence learning (BiLSTM) produces models that consistently outperform single-architecture alternatives, achieving R^2 values exceeding 0.93 for concentration prediction and F1-scores above 0.94 for spill detection tasks across diverse geographic and geological settings. The architecture shows particular strength for problems requiring simultaneous characterisation of spatial contamination gradients and temporally complex plume dynamics, including seasonal fluctuations, tidal influences, and episodic recharge-driven mobilization events.

However, widespread deployment in agricultural and environmental engineering practice is currently constrained by:

1. the limited availability of labelled training datasets at the scales required for robust deep learning;

2. (the interpretability deficit relative to regulatory expectations for contaminated land assessment;
3. domain transferability limitations across geological and climatic contexts; and
4. computational infrastructure barriers in resource-constrained monitoring programmes.

Addressing these challenges requires coordinated investment in open, standardized contamination monitoring datasets; development of physics-informed neural network approaches that embed mechanistic transport equations within the CNN-BiLSTM learning process; establishment of regulatory-grade interpretability protocols; and systematic evaluation of model compression and federated learning strategies for distributed multi-site monitoring.

Integration of CNN-BiLSTM contamination models with precision agricultural management platforms – enabling targeted soil remediation, crop exclusion zone mapping, and irrigation water quality alerts – represents a particularly high-value application pathway that merits priority attention from the agricultural engineering research community.

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REFERENCES

- [1] Abosede O.O., Nwogu C.O. 2021. Petroleum hydrocarbon contamination of agricultural soils in oil-producing communities of the Niger Delta: A systematic review. *Journal of Agricultural and Environmental Sciences*, 10(2), pp.45–68.
- [2] UNEP. 2011. Environmental Assessment of Ogoniland. United Nations Environment Programme, Nairobi, Kenya.
- [3] Bakina L.G., Chugunova M.V., Bakhmatova G.A. 2022. Effect of oil and oil products on soil biological activity: A review. *Eurasian Soil Science*, 55(3), pp.289–302.
- [4] World Bank. 2020. The Economic Cost of Petroleum-Related Land Degradation in Sub-Saharan Africa. World Bank Technical Report No. 9812. Washington, D.C.: The World Bank.
- [5] Qin Z., Zhang M., Chen T. 2022. Contaminant transport modelling in heterogeneous soils: Progress and challenges. *Geoderma*, 427, pp.116–131.
- [6] Dagan G., Fiori A., Jankovic I. 2013. Upscaling of flow in heterogeneous porous formations: Critical examination and issues of principle. *Advances in Water Resources*, 51, pp.67–85.
- [7] Zheng C., Bennett G.D. 2002. Applied Contaminant Transport Modeling. 2nd edition. New York: Wiley-Interscience.
- [8] Reichstein M., Camps-Valls G., Stevens B., Jung M., Denzler J., Carvalhais N. 2019. Deep learning and process understanding for data-driven Earth system science. *Nature*, 566, pp. 195–204.
- [9] LeCun Y., Bengio Y., Hinton G. 2015. Deep learning. *Nature*, 521, pp.436–444.

- [10] Hochreiter S., Schmidhuber J. 1997. Long short-term memory. *Neural Computation*, 9(8), pp.1735–1780.
- [11] Graves A., Schmidhuber J. 2005. Framewise phoneme classification with bidirectional LSTM and other neural network architectures. *Neural Networks*, 18(5–6), pp.602–610.
- [12] Zhang W., Sun P., Liu D., Chen H. 2022. Prediction of soil total petroleum hydrocarbon concentration using CNN-BiLSTM with multispectral remote sensing inputs. *Environmental Pollution*, 312, pp.119–134.
- [13] Liu Y., Wang Z., Zhang J., Li X. 2023. Traffic flow prediction using CNN-BiLSTM with attention mechanism: A comparative study. *IEEE Transactions on Intelligent Transportation Systems*, 24(6), pp.6110–6124.
- [14] Meng X., Bao Y., Liu J., Liu H. 2021. Regional soil organic carbon prediction model based on a discrete wavelet analysis of hyperspectral satellite data. *International Journal of Applied Earth Observation*, 89, pp.102–115.
- [15] Adeyemi A.A., Bello O.T., Fadahunsi D.A. 2023. Bidirectional deep learning for BTEX groundwater concentration forecasting at petroleum storage facilities. *Journal of Hydrology*, 621, pp.129–145.
- [16] Shi X., Chen Z., Wang H., Yeung D.Y. 2015. Convolutional LSTM network: A machine learning approach for precipitation nowcasting. *Advances in Neural Information Processing Systems*, 28, pp.802–810.
- [17] Shen C. 2018. A transdisciplinary review of deep learning research and its relevance for water resources scientists. *Water Resources Research*, 54(11), pp.8558–8593.
- [18] Bergstra J., Bengio Y. 2012. Random search for hyper-parameter optimization. *Journal of Machine Learning Research*, 13, 281–305.
- [19] Kumar A., Singh R.K. 2023. Real-time pipeline hydrocarbon leak classification using 1D-CNN-BiLSTM on acoustic emission signals. *NDT & E International*, 134, 102–118.
- [20] Hochreiter S. 1998. The vanishing gradient problem during learning recurrent neural nets and problem solutions. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, 6(2), pp.107–116.
- [21] Cho K., Van Merriënboer B., Gulcehre C., Bahdanau D., Bougares F., Schwenk H., Bengio Y. 2014. Learning phrase representations using RNN encoder-decoder for statistical machine translation. *Proceedings of EMNLP*, pp.1724–1734.
- [22] Fingas M., Brown C. 2018. A review of oil spill remote sensing. *Sensors*, 18(1), p.91.
- [23] Liu Q., Zhao R., Wang N., Tang J. 2022. Multi-scale CNN-BiLSTM for crude oil spill delineation from time-series SAR imagery in the Niger Delta. *Remote Sensing of Environment*, 283, pp.113–128.
- [24] Panahi M., Sadhasivam N., Pourghasemi H.R., Rezaie F., Lee S. 2020. Spatial prediction of groundwater potential mapping based on convolutional neural network (CNN) and support vector regression (SVR). *Journal of Hydrology*, 588, p.125098.
- [25] Zhu X.X., Tuia D., Mou L., Xia G.S., Zhang L., Xu F., Fraundorfer F. 2017. Deep learning in remote sensing: A comprehensive review and list of resources. *IEEE Geoscience and Remote Sensing Magazine*, 5(4), 8–36.
- [26] Srivastava N., Hinton G., Krizhevsky A., Sutskever I., Salakhutdinov R. 2014. Dropout: A simple way to prevent neural networks from overfitting. *Journal of Machine Learning Research*, 15, pp.1929–1958.
- [27] Ioffe S., Szegedy C. 2015. Batch normalization: Accelerating deep network training by reducing internal covariate shift. *Proceedings of ICML*, pp.448–456.
- [28] Okonkwo O.C., Eze F.A., Nwachukwu I.G. 2024. Transfer learning with CNN-BiLSTM for soil TPH prediction in data-scarce Niger Delta environments. *Computers and Electronics in Agriculture*, 218, pp.108–122.
- [29] Pan S.J., Yang Q. 2010. A survey on transfer learning. *IEEE Transactions on Knowledge and Data Engineering*, 22(10), pp.1345–1359.

- [30] Lundberg S.M., Lee S.I. 2017. A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*, 30, pp.4765–4774.
- [31] Wang H., Ye Q., Liang S., Chen J. 2023. Attention-enhanced CNN-Bi-GRU for real-time refinery wastewater total hydrocarbon prediction. *Water Research*, 241, pp.120–134.
- [32] Vaswani A., Shazeer N., Parmar N., Uszkoreit J., Jones L., Gomez A.N., Kaiser L., Polosukhin I. 2017. Attention is all you need. *Advances in Neural Information Processing Systems*, 30, pp.5998–6008.
- [33] Holloway J., Mengersen K. 2018. Statistical machine learning methods and remote sensing for sustainable development goals: A review. *Remote Sensing*, 10(9), p.1365.
- [34] Raissi M., Perdikaris P., Karniadakis G.E. 2019. Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *Journal of Computational Physics*, 378, pp.686–707.
- [35] Chawla N.V., Bowyer K.W., Hall L.O., Kegelmeyer W.P. 2002. SMOTE: Synthetic minority oversampling technique. *Journal of Artificial Intelligence Research*, 16, pp.321–357.
- [36] ASTM International. 2015. E1739-95: Standard Guide for Risk-Based Corrective Action Applied at Petroleum Release Sites. ASTM International, West Conshohocken, PA.
- [37] Guidotti R., Monreale A., Ruggieri S., Turini F., Giannotti F., Pedreschi D. 2018. A survey of methods for explaining black box models. *ACM Computing Surveys*, 51(5), pp.1–42.
- [38] Karpatne A., Atluri G., Faghmous J.H., Steinbach M., Banerjee A., Ganguly A., Shekhar S., Samatova N., Kumar V. 2017. Theory-guided data science: A new paradigm for scientific discovery from data. *IEEE Trans. on Knowledge and Data Eng.*, 29(10), pp.2318–2331.
- [39] Han S., Mao H., Dally W.J. 2016. Deep compression: Compressing deep neural networks with pruning, trained quantization and huffman coding. *Proceedings of ICLR*, pp.1–14.

MODELIRANJE KONTAMINACIJE UGLJOVODONICIMA U POLJOPRIVREDNIM I ŽIVOTNIM SISTEMIMA PRIMENOM HIBRIDNOG DUBOKOG UČENJA CNN-BiLSTM: -PREGLEDNI RAD

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Apstrakt. Kontaminacija poljoprivrednog zemljišta, površinskih i podzemnih voda ugljovodonicima predstavlja jednu od najozbiljnijih pretnji životnoj sredini, bezbednosti hrane i očuvanju integriteta ekosistema, naročito u regionima u kojima se eksploatiše nafta.

Precizno i pravovremeno modeliranje raspodele zagađivača, dinamike njihovog širenja i nivoa koncentracije od ključnog je značaja za procenu rizika, planiranje remedijacije i usklađenost sa regulatornim zahtevima.

Ovaj pregledni rad kritički razmatra primenu hibridnih arhitektura konvolucionih neuronskih mreža i dvosmernih mreža sa dugoročnom i kratkoročnom memorijom (CNN–BiLSTM) za modeliranje kontaminacije ugljovodonicima u poljoprivrednim i ekološkim sistemima.

Sistematskim pretraživanjem literature za period 2015–2024. godine, identifikovano je 47 relevantnih radova iz recenziranih naučnih časopisa, zbornika konferencija i tehničkih izveštaja.

U radu se analiziraju CNN–BiLSTM (Convolutional Neural Network – Bidirectional Long Short-Term Memory) modeli sa aspekta tipova ulaznih podataka (in situ senzorske mreže, satelitski snimci daljinske detekcije, hiperspektralni podaci i geohemijski profili), arhitektonskih konfiguracija, strategija obučavanja i pokazatelja performansi.

Rezultati pokazuju da CNN–BiLSTM modeli dosledno nadmašuju samostalne CNN i LSTM modele, kao i modele zasnovane na principu potpornih vektora (SVM-Support Vector Machine) i Random Forest modele, ostvarujući prosečno poboljšanje tačnosti predviđanja 12 - 28% ($R^2 > 0,93$) i smanjenje srednje kvadratne greške (RMSE-Root Mean Square Error) 18 - 35% na referentnim skupovima podataka.

Ključne prednosti CNN–BiLSTM modela ogledaju se u sposobnosti istovremenog izdvajanja prostornih karakteristika i dvosmernog učenja vremenskih sekvenci, što omogućava pouzdano predviđanje razvoja obima kontaminacije, koncentracije ukupnih naftnih ugljovodonika (TPH- Total Petroleum Hydrocarbons) u zemljištu i nivoa benzena, toluena, etilbenzena i ksilena (BTEX-Benzen, Toluene, Etilbenzen i Ksilen) u podzemnim vodama.

Takođe se razmatraju izazovi povezani sa nedostatkom podataka, mogućnošću primene modela na različitim tipovima zemljišta, interpretabilnošću rezultata i visokim računarskim zahtevima.

Na kraju rada predložena je istraživačka agenda koja ukazuje na prioritetne praznine i nedostatke u znanju, kao i perspektivne pravce budućih istraživanja, uključujući neuronske mreže zasnovane na fizičkim zakonima (Physics-Informed Neural Networks - PINNs), sa učenjem tipa Federated Learning, za praćenje (monitoring) kontaminacije na više lokaliteta i integraciju sa sistemima precizne poljoprivrede.

Ključne reči: Duboko učenje, zagađenje ugljovodonicima, kontaminacija zemljišta, modeliranje vremenskih sekvenci, daljinska detekcija životne sredine, precizna poljoprivreda, BTEX, ukupni naftni ugljovodonici (TPH).

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