

DAFTAR PUSTAKA

- [1] S. Sarwono, Lukas, M. A. Kartawidjaja, and R. S. Wardana, “Stuck Pipe Detection in Geothermal Operation with Support Vector Machine,” *J. Earth Energy Eng.*, vol. 11, no. 2, Sept. 2022, doi: 10.25299/jeee.2022.9258.
- [2] S. Zhu, X. Song, Z. Zhu, X. Yao, and M. Liu, “Intelligent Prediction of Stuck Pipe Using Combined Data-Driven and Knowledge-Driven Model,” *Appl. Sci.*, vol. 12, no. 10, p. 5282, May 2022, doi: 10.3390/app12105282.
- [3] K. R. Mopuri *et al.*, “Early sign detection for the stuck pipe scenarios using unsupervised deep learning,” *J. Pet. Sci. Eng.*, vol. 208, p. 109489, Jan. 2022, doi: 10.1016/j.petrol.2021.109489.
- [4] B. Elahifar and E. Hosseini, “Machine learning algorithm for prediction of stuck pipe incidents using statistical data: case study in middle east oil fields,” *J. Pet. Explor. Prod. Technol.*, vol. 12, no. 7, pp. 2019–2045, July 2022, doi: 10.1007/s13202-021-01436-3.
- [5] Q. K. Do, T. Q. Hoang, T. Nguyen, and V. K. P. Ong, “Predicting and avoiding hazardous occurrences of stuck pipe for the petroleum wells at offshore Vietnam using machine learning techniques,” *IOP Conf. Ser. Earth Environ. Sci.*, vol. 1091, no. 1, p. 012003, Nov. 2022, doi: 10.1088/1755-1315/1091/1/012003.
- [6] J. Duan, Y. Tian, E. Long, and W. Long, “A Model for Early Detection of Stuck Pipe Using Random Forest Algorithm,” Feb. 14, 2023, *Springer Science and Business Media LLC*. doi: 10.21203/rs.3.rs-2528515/v1.
- [7] X. Zhang *et al.*, “Identification Method of Stuck Pipe Based on Data Augmentation and ATT-LSTM,” *Processes*, vol. 12, no. 7, p. 1296, June 2024, doi: 10.3390/pr12071296.
- [8] H. N. Al-Mamoori, J. Tian, and H. Ma, “Stuck Pipe Detection in Oil and Gas Drilling Operations Using Deep Learning Autoencoder for Anomaly Diagnosis,” *Appl. Sci.*, vol. 15, no. 9, p. 5042, May 2025, doi: 10.3390/app15095042.
- [9] D. Rosiani, Zulfan, B. Y. Suranta, A. Sofyan, F. G. Pradana, and R. B. Putra, “Machine Learning Classifies Data for Early Warning of Stuck Pipe Detection in Geothermal Drilling,” *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 15, no. 1, pp. 44–51, Feb. 2025, doi: 10.18517/ijaseit.15.1.20333.
- [10] A. Taqi and A. Assi, “Utilizing Artificial Neural Networks to Predict Stuck Pipe in Southern

- Iraq Oil Fields,” *Iraqi Geol. J.*, pp. 109–129, Jan. 2025, doi: 10.46717/igj.58.1a.8ms-2025-1-18.
- [11] S. Sinha and Y. M. Lee, “Challenges with developing and deploying AI models and applications in industrial systems,” *Discov. Artif. Intell.*, vol. 4, no. 1, Aug. 2024, doi: 10.1007/s44163-024-00151-2.
- [12] AMOCO, *Training to Reduce Unscheduled Events*. in Third Edition. 1996.
- [13] T. Zhang, Y. Xue, Z. Meng, M. Sader, W. Zhang, and J. Li, “Drill Sticking Prediction Based on Modal Decomposition and Physical Constraint Model of Near-Bit Data,” *Processes*, vol. 13, no. 6, p. 1802, June 2025, doi: 10.3390/pr13061802.
- [14] H. H. Elmousalami and M. Elaskary, “Drilling stuck pipe classification and mitigation in the Gulf of Suez oil fields using artificial intelligence,” *J. Pet. Explor. Prod. Technol.*, vol. 10, no. 5, pp. 2055–2068, June 2020, doi: 10.1007/s13202-020-00857-w.
- [15] “Drill String Components Guide In Oil & Gas - Drilling Manual.” Accessed: July 22, 2025. [Online]. Available: <https://www.drillingmanual.com/drill-string-overview/>
- [16] S. D’Amicis, M. Pagani, M. Matteucci, L. Piroddi, A. Spelta, and F. Zausa, “Stuck pipe prediction from rare events in oil drilling operations,” *Upstream Oil Gas Technol.*, vol. 11, p. 100096, Sept. 2023, doi: 10.1016/j.upstre.2023.100096.
- [17] A. C. Montes, P. Ashok, and E. Van Oort, “Review of Stuck Pipe Prediction Methods and Future Directions,” *SPE J.*, vol. 30, no. 06, pp. 3334–3363, June 2025, doi: 10.2118/220725-pa.
- [18] “Understanding LSTM Networks -- colah’s blog.” Accessed: July 22, 2025. [Online]. Available: <https://colah.github.io/posts/2015-08-Understanding-LSTMs/>
- [19] N. Srivastava, E. Mansimov, and R. Salakhutdinov, “Unsupervised Learning of Video Representations using LSTMs,” Jan. 04, 2016, *arXiv*: arXiv:1502.04681. doi: 10.48550/arXiv.1502.04681.
- [20] “Recurrent Neural Network (RNN) – Part 5: Custom Cells – The Neural Perspective.” Accessed: July 22, 2025. [Online]. Available: <https://theneuralperspective.wordpress.com/2016/11/17/recurrent-neural-network-rnn-part-4-custom-cells/>
- [21] R. Dey and F. M. Salem, “Gate-variants of Gated Recurrent Unit (GRU) neural networks,” in *2017 IEEE 60th International Midwest Symposium on Circuits and Systems (MWSCAS)*,

Boston, MA: IEEE, Aug. 2017, pp. 1597–1600. doi: 10.1109/mwscas.2017.8053243.

- [22] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, “Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling,” Dec. 11, 2014, *arXiv*: arXiv:1412.3555. doi: 10.48550/arXiv.1412.3555.
- [23] M. Sokolova and G. Lapalme, “A systematic analysis of performance measures for classification tasks,” *Inf. Process. Manag.*, vol. 45, no. 4, pp. 427–437, July 2009, doi: 10.1016/j.ipm.2009.03.002.
- [24] R. R. Rakhimov, O. V. Zhdaneev, K. N. Frolov, and M. P. Babich, “Stuck Pipe Early Detection on Extended Reach Wells Using Ensemble Method of Machine Learning,” in *SPE Russian Petroleum Technology Conference*, Virtual: SPE, Oct. 2021. doi: 10.2118/206516-ms.
- [25] R. Wirth and J. Hipp, “CRISP-DM: Towards a Standard Process Model for Data Mining”.
- [26] A. M. Shimaoka, R. C. Ferreira, and A. Goldman, “The evolution of CRISP-DM for Data Science: Methods, Processes and Frameworks,” *SBC Rev. Comput. Sci.*, vol. 4, no. 1, pp. 28–43, Oct. 2024, doi: 10.5753/reviews.2024.3757.
- [27] “IEEE Standard Glossary of Software Engineering Terminology.”
- [28] M. Rettig, “Prototyping for tiny fingers,” *Commun. ACM*, vol. 37, no. 4, pp. 21–27, Apr. 1994, doi: 10.1145/175276.175288.
- [29] “The Data File Format - Structural Vibration Solutions.” Accessed: July 22, 2025. [Online]. Available: <https://www.svibs.com/the-data-file-format/>
- [30] A. A. A. Abdullah M, R. Roy, S. P V, K. Krishnan O, and J. Joseph, “Analysis of pipe sticking due to wellbore uncleanliness using machine learning,” *Heliyon*, vol. 9, no. 12, p. e22366, Dec. 2023, doi: 10.1016/j.heliyon.2023.e22366.
- [31] M. Ahsan, M. Mahmud, P. Saha, K. Gupta, and Z. Siddique, “Effect of Data Scaling Methods on Machine Learning Algorithms and Model Performance,” *Technologies*, vol. 9, no. 3, p. 52, July 2021, doi: 10.3390/technologies9030052.
- [32] O. Al-Debagy and P. Martinek, “A Comparative Review of Microservices and Monolithic Architectures,” in *2018 IEEE 18th International Symposium on Computational Intelligence and Informatics (CINTI)*, Budapest, Hungary: IEEE, Nov. 2018. doi: 10.1109/cinti.2018.8928192.
- [33] H. da Gĩa, A. Flores, R. Pereira, and J. Cunha, “Chronicles of CI/CD: A Deep Dive into its



Usage Over Time,” Feb. 27, 2024, *arXiv*: arXiv:2402.17588. doi: 10.48550/arXiv.2402.17588.

- [34] O. S. Ahmed, B. M. Aman, M. A. Zahrani, and F. I. Ajikobi, “Stuck Pipe Early Warning System Utilizing Moving Window Machine Learning Approach,” in *Abu Dhabi International Petroleum Exhibition & Conference*, Abu Dhabi, UAE: SPE, Nov. 2019. doi: 10.2118/197674-ms.
- [35] W. Li and K. L. E. Law, “Deep Learning Models for Time Series Forecasting: A Review,” *IEEE Access*, vol. 12, pp. 92306–92327, 2024, doi: 10.1109/access.2024.3422528.
- [36] K. Cho *et al.*, “Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation,” Sept. 03, 2014, *arXiv*: arXiv:1406.1078. doi: 10.48550/arXiv.1406.1078.
- [37] “Stateful LSTM in Keras – Philippe Remy – My Blog.” Accessed: July 22, 2025. [Online]. Available: <https://philipperemy.github.io/keras-stateful-lstm/>
- [38] Y. Bengio, P. Simard, and P. Frasconi, “Learning Long-Term Dependencies with Gradient Descent is Difficult,” *IEEE Access*, vol. 5, p. 166, 1994, doi: 10.1109/72.279181.
- [39] W. Chen, K. Yang, Z. Yu, Y. Shi, and C. L. P. Chen, “A survey on imbalanced learning: latest research, applications and future directions,” *Artif. Intell. Rev.*, vol. 57, no. 6, May 2024, doi: 10.1007/s10462-024-10759-6.
- [40] M. Openja, A. Nikanjam, A. H. Yahmed, F. Khomh, Z. Ming, and Jiang, “An Empirical Study of Challenges in Converting Deep Learning Models,” June 28, 2022, *arXiv*: arXiv:2206.14322. doi: 10.48550/arXiv.2206.14322.