Global Journal of Engineering, Design & Technology
ISSN: 2319-7293
OPEN ACCESS Freely available online

Commentary

Enhancing Engineering Efficiency with Machine Learning

Daniele Rapetti*

Department of Computer Engineering, Bosphorus University, Istanbul, Turkey

ABOUT THE STUDY

Machine learning is an emerging technology that has revolutionized the way engineers approach problems. It has become a crucial tool in engineering, and it has found applications in various fields, from manufacturing to energy, aerospace, and biomedical engineering.

Machine learning refers to a subset of artificial intelligence that enables machines to learn from data and improve their performance over time. Machine learning algorithms are created to recognize patterns in data, predict the future, or take action without being explicitly programmed. In other words, machines can learn to perform tasks by recognizing patterns and relationships in data, without the need for human intervention.

In engineering, machine learning is used to analyses large datasets, predict outcomes, optimize processes, and improve efficiency [1,2]. For example, machine learning can be used to analyses sensor data from industrial equipment to detect anomalies and predict failures. It can also be used to optimize the design of complex systems, such as aircraft engines, by simulating various scenarios and identifying the most efficient designs.

One of the main advantages of machine learning is its ability to handle large amounts of data. With the increase in data availability, machine learning has become an essential tool for engineers to extract insights and make informed decisions [3,4]. Machine learning algorithms can analyses vast amounts of data from various sources, such as sensors, cameras, and databases, to identify patterns, anomalies, and trends [5].

Another advantage of machine learning is its ability to learn from experience. Machine learning algorithms can be trained on historical data to learn patterns and make predictions. For example, in manufacturing, machine learning can be used to predict defects or failures in products based on past production data [6,7]. This allows engineers to identify and address issues before they occur, improving product quality and reducing costs.

Machine learning is also used to optimize processes and improve efficiency. For example, in energy production, machine learning can be used to predict energy demand and optimize production schedules. In transportation, machine learning can be used to optimize routes, reduce travel time, and minimize fuel consumption [8].

One of the challenges of machine learning in engineering is the need for high-quality data. Machine learning algorithms require large amounts of data to train and make accurate predictions. However, the quality of the data is essential, as machine learning algorithms can be sensitive to outliers, noise, and biases in the data [9]. Therefore, engineers need to ensure that the data is representative, accurate, and reliable. Another challenge of machine learning in engineering is the interpretability of the results. Machine learning algorithms can be complex, and it can be difficult to understand how they make predictions or decisions. Therefore, engineers need to ensure that the results are interpretable and can be explained to stakeholders [10].

To address these challenges, engineers have developed various techniques and tools to improve the quality of data and interpretability of results. For example, data pre-processing techniques are used to clean, normalize, and transform data before it is fed into machine learning algorithms. Feature selection techniques are used to identify the most relevant features in the data to improve model accuracy and reduce complexity. Model interpretation techniques are used to understand how machine learning algorithms make decisions or predictions, allowing engineers to improve the model's performance and explain its behavior to stakeholders [11].

Machine learning has become an essential tool for engineers in various fields. It has enabled engineers to analyses large datasets, predict outcomes, optimize processes, and improve efficiency [12]. Machine learning has also introduced new challenges, such as the need for high-quality data and interpretability of results. However, with the development of new techniques and tools, engineers can overcome these challenges and continue to leverage the power of machine learning in engineering.

REFERENCES

1. Gigante CM, Yale G, Condori RE, Costa NC, Long NV, Minh PQ, et al. Portable rabies virus sequencing in canine rabies endemic

Correspondence to: Daniele Rapetti, Department of Computer Engineering, Bosphorus University, Istanbul, Turkey, E-mail: RapettiD1999@yahoo.com

Received: 10-Feb-2023, Manuscript No. GJEDT-23-22927; **Editor assigned:** 13-Feb-2023, PreQC No. GJEDT-23-22927 (PQ); **Reviewed:** 28-Feb-2023, QC No. GJEDT-23-22927; **Revised:** 07-Mar-2023, Manuscript No. GJEDT-23-22927 (R); **Published:** 14-Mar-2023, DOI: 10.35248/2319-7293.23.12.166

Citation: Rapetti D (2023) Enhancing Engineering Efficiency with Machine Learning. Global J Eng Des Technol. 12:166

countries using the Oxford Nanopore MinION. Viruses. 2020; 12(11):1255.

2. Jain M, Koren S, Miga KH, Quick J, Rand AC, Sasani TA, et al. Nanopore sequencing and assembly of a human genome with ultra-long reads. Nat Biotechnol. 2018; 36(4):338-45.
3. Miga KH, Koren S, Rhie A, Vollger MR, Gershman A, Bzikadze A, et al. Telomere-to-telomere assembly of a complete human X chromosome. Nature. 2020; 585(7823):79-84.
4. Bednarski Ł, Sieńko R, Howiacki T. Analysis of rheological phenomena in reinforced concrete cross-section of Rędziński bridge pylon based on *in situ* measurements. Procedia Eng. 2015; 108:536-543.
5. Mu HQ, Liang XX, Shen JH, Zhang FL. Analysis of Structural Health Monitoring Data with Correlated Measurement Error by Bayesian System Identification: Theory and Application. Sensors. 2022;22(20):7981.
6. Bednarski Ł, Sieńko R, Grygierek M, Howiacki T. New distributed fibre optic 3DSensor with thermal self-compensation system: design, research and field proof application inside geotechnical structure. Sensors. 2021;21(15):5089.
7. Liu Y, Li X, Li H, Fan X. Global temperature sensing for an operating power transformer based on Raman scattering. Sensors. 2020;20(17):4903.
8. Coscetta A, Catalano E, Cerri E, Oliveira R, Bilro L, Zeni L, et al. Distributed Static and Dynamic Strain Measurements in Polymer Optical Fibers by Rayleigh Scattering. Sensors. 2021;21(15):5049.
9. Barrias A, Casas JR, Villalba S. A review of distributed optical fiber sensors for civil engineering applications. Sensors. 2016;16(5):748.
10. Zhou DP, Li W, Chen L, Bao X. Distributed temperature and strain discrimination with stimulated Brillouin scattering and Rayleigh backscatter in an optical fiber. Sensors. 2013;13(2):1836-1845.
11. Bao X, Chen L. Recent progress in Brillouin scattering based fiber sensors. Sensors. 2011;11(4):4152-4187.
12. Yan B, Li J, Zhang M, Zhang J, Qiao L, Wang T. Raman distributed temperature sensor with optical dynamic difference compensation and visual localization technology for tunnel fire detection. Sensors. 2019;19(10):2320.