International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Application of Artificial Intelligence in Engineering: A Comprehensive Review

[1] Valluri Daneesha, [2] S. Balamuralitharan, [3] Santhoshkumar S., [4] Dr Someshwar Siddi, [5] T Prabhakara Rao

Submitted: 07/01/2024 **Revised:** 27/02/2024 **Accepted:** 08/03/2024

Abstract— Artificial intelligence (AI) is changing engineering due to automating complex procedures, refining the design optimization, enhancing decision-making, and implementing predictive maintenance. This paper summarizes state of the art application of AI to several different disciplines of engineering such as civil, mechanical, electrical, and computer engineering. From the review, one can see the merging of machine learning, deep learning, computer vision, and natural language processing into solving traditional engineering problems. Important developments, tools, frameworks, and implementations into real life cases are analyzed to reveal what is trendy nowadays and what can be projected in the future. The research comes to a conclusion that AI does not only enhance efficiency and precision in engineering processes, but it also spurs innovation by means of intelligent automation and data insights.

Keywords*— Artificial Intelligence, Engineering Applications, Machine Learning, Deep Learning, Predictive Maintenance, Automation, Smart Design, Data-Driven Engineering*

I. INTRODUCTION

The combination of Artificial Intelligence (AI), and engineering has brought about a total paradigm change in the way issues are analyzed, systems engineered, and solutions implemented. Engineering has relied on deterministic models, mathematical rigour and empirical testing. But the upsurge of complexity in engineering problems, in addition to the explosion of sensor data, simulation, digital infrastructure, has made the traditional methods less adequate alone. AI opens up the new paradigm – the one based on pattern recognition, predictive analytics, automation, and continuous learning [11-15].

AI stands for the ability of machines to do what is traditionally considered the function of a human mind, namely to read natural language, find patterns, learn from the data, and make decisions. With such subfields as machine learning (ML), deep learning (DL), reinforcement learning (RL), and natural language processing (NLP), it is now possible to customize AI systems to diverse engineering applications. This flexibility is important in today's engineering disciplines where problems are multi-dimensional and there is often need for real time solutions.

In, for example, the civil engineering, AI is applied to forecast infrastructure decay as well as to analyze traffic patterns and urban resources management more effectively. AI in mechanical engineering is being used to facilitate predictive maintenance of industrial machinery, intelligent manufacturing system, and autonomous robotics. Electrical engineering makes use of AI for power grid governance, renewable energy enhancement, and fault detection, and computer engineering receives the advantage of AI in cybersecurity, software development and embedded system field.

[1]Research Scholar, Department of Computer Science Engineering, Delhi Technological University, Shahbad Daulapur, Delhi - 110042
daneesha.valluri@gmail.com
[2]Adjunct Faculty, Department of Pure and Applied Mathematics, Saveetha School of Engineering, SIMATS, Chennai, Tamil Nadu, India
Email Id: balamurali.maths@gmail.com
[3]Assistant Professor, Department of Mathematics, Patrician College of Arts and Science, Chennai, India
santhoshkumarsesa@gmail.com
[4]Associate Professor, Department of FME, St. Martin's Engineering College, Dhulapally, Secunderabad-500100
someshsiddi@gmail.com
[5]Associate Professor, Department of Computer Science & Engineering, Aditya University, Surampalem, India, prabhakararaot@aec.edu.in

The application of AI to engineering procedures has transitioned from demonstrative experiments to the actual use in the real world. From automated design optimization to real-time system monitoring, AI tools are aimed at minimizing human error, decreasing costs, and increasing sustainability for engineers. Meanwhile, AI is pushing the envelope on what is possible in engineering, helping to drive innovation in smart cities, autonomous vehicles, advanced materials, and precision manufacturing [8].

Despite the progress, challenges persist. Engineering domains are high-stakes domains where safety, reliability, and transparency are important. Not only are AI models "black-box" in many cases, especially in the case of deep learning systems, but their interpretability and accountability is questionable. Also, the process of integrating AI into old systems and old workflows can be technically challenging and culturally challenging. Engineers should acquire new skills in data science, algorithm design and AI ethics to make maximum use of the technologies.

This broad review aims at mapping the landscape of AI applications in the major engineering disciplines. It draws scattered literature together, identifies key technologies, assesses real case studies in the field, and considers the opportunities and obstacles to AI implementation in engineering. The objective is to deliver to scholars and practitioners an informed insight that could be used to inform future research, education, and industrial application [9].

By providing a cross-domainal view, this paper also shows the universality of AI while at the same time recognizing the domain-specific needs of each of the engineering disciplines. No matter if it is through a supervised learning process for structural modeling, or convolutional neural networks for image-based inspection, or for system optimization, genetic algorithms, AI is making available a continually expanding toolset for engineers. This cooperation between AI and engineering is not just improving efficiency – it is redefining the engineer's imagination, practice, and accomplishment [6].

Novelty and Contribution

Some of the new insights provided in this review paper as well as the unique contributions that this review paper makes to the field include:

1. Cross-Disciplinary Integration: Unlike the numerous current studies that delve only in a particular development of engineering, this paper offers an integrated framework to study the AI applications in civil, mechanical, electrical, and computer engineering. This approach concerning various spheres assists in finding shared approaches to their resolution as well as disclosing transferable tactics.
2. Consolidation of Recent Advances: The paper combines recent developments from the period of 2015-2024, who include both academic research studies and industrial implementation. Through examining the most recent trends, tools, and frameworks, it becomes a modern and up-to-date source of reference for researchers and engineers.
3. Holistic Methodological Overview: This work is not just a list of applications; it explores the basic AI techniques (e.g., supervised learning, reinforcement learning, computer vision, and NLP) and put them to relevant engineering tasks. Such a clear outline of the methodology serves as the guidance for practitioners, allowing them to understand which of the AI methods will be the most appropriate for a specific problem.
4. Detection of Research Gaps and Difficulties. By combining findings from different disciplines, the paper brings not only the achievements, but also the existing limitations, the lack of interpretability in AI models, difficulties in integration of AI with legacy systems, and the necessity of ethical frameworks. The insights can guide future research agendas [2].
5. Framework for Future Implementation: The paper describes a conceptual map of how AI can be systematically integrated with the engineering workflows. It covers such steps as data acquisition, model selection, training-validation-testing cycles and deployment considerations – covering the gap between AI theory and engineering practice.
6. Industry-Academia Synergy: The paper can thus appeal to both researchers and practitioners as both academical and industry case study literature is provided. This coupled focus triggers collaboration between universities and engineering companies.

Summarily, this paper also adds value, not only when reviewing literature, but synthesizing it in a coherent story that can identify trends, explain methodologies and provide actionable insights. It acts as a basic resource and a strategic map for the emerging fusion of AI with engineering.

II. RELATED WORKS

In 2022 R. Ahmed et.al., S. Shaheen et.al., and S. P. Philbin et.al. [10] suggested the use of Artificial Intelligence in engineering has been gaining momentum in all fronts thanks to its ability to perform complex computations, optimizing designs and for providing intelligent automation. In civil engineering, the use of machine learning methods to predict the material properties, evaluate the integrity of structures and improve construction management has been proven in the past. AI models have been applied for such purposes as prediction of concrete strength, building damage evaluation post-disaster, optimization of transportation system on the basis of real time data analytics.

In 2022 S. Tiwari et.al., [7] introduced the areas where the mechanical engineering studies have been concentrating on the usage of the AI are predictive maintenance, quality control, and computer-aided design. Machine learning algorithms are trained using sensor data, which predicts equipment breakdown hence reducing time of downtime. Intelligent systems also facilitate generative design processes when AI comes in to aid in the generation of several alternatives for a design according to given constraints, and thus improving product performance while material waste is minimized.

In an electrical engineering field, AI has had a useful hand in enhancing efficiency and endurance in power systems. Some of the AI procedures are utilized in load forecasting, fault detection, energy management, and smart grid operations. Adaptive algorithms optimize the usage of energy in accordance with the consumption patterns, whereas computer vision and models of deep learning facilitate the supervision of transmission infrastructure and anomaly detection.

In 2022 F. Artkin et.al., [1] proposed the AI has to a great extent been adopted by computer and software engineering fields in tasks like automatic generation of codes, anomaly detection, software testing, and cybersecurity. The use of AI-based systems is to discover the weaknesses in codes, detect malware, and enable intelligent decision-in-the-network management. In addition, there have been the natural language processing methods which have led to the creation of the AI-powered development assistants and bug fix generators.

Up to this point, although significant advancement has been made, the majority of available literature has been considering isolated applications of a domain-specific nature. A substantial integration of AI mechanism techniques and their implementations in engineering are considerably scarce. Furthermore, although various studies tend to define the performance of separate AI models, the works still lack the discussions on integration difficulties, ethical issues, or the long-term feasibility of AI-based engineering systems.

III. PROPOSED METHODOLOGY

To systematize the integration of Al in engineering workflows, we propose a modular methodology that involves four primary stages: data acquisition, preprocessing, model selection and training, and deployment. Each stage is mathematically formulated to provide clarity, reproducibility, and scalability across various engineering domains [3].

A. Data Acquisition and Representation

Engineering datasets often consist of structured sensor readings, unstructured visual data, or mixed-mode input. Let the input dataset be represented as:

$$D = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$$

where x_i is the input feature vector and y_i is the corresponding target output.

For image-based or spatial data common in civil and mechanical engineering, we define a pixel grid input as:

$$I_{m\times n} = \sum_{i=1}^{m} \sum_{j=1}^{n} p_{ij}$$

where p_{ij} represents the pixel intensity at position (i, j).

B. Preprocessing and Normalization

Raw engineering data often contains noise and outliers. Normalization is crucial to ensure balanced learning. A common min-max normalization is given by:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

For standardization in mechanical load datasets, we often use z-score normalization:

$$z = \frac{x - \mu}{\sigma}$$

where μ is the mean and σ is the standard deviation.

C. Model Selection and Learning

We adopt supervised learning approaches for classification and regression in design optimization, failure prediction, and process control. A basic linear regression model is given by:

$$\hat{y} = \beta_0 + \beta_1 x$$

For multi-variable engineering tasks, multiple linear regression is used:

$$\hat{y} = \beta_0 + \sum_{i=1}^{n} \beta_i x_i$$

In cases requiring non-linearity, a neural network output is calculated as:

$$y = f(Wx + b)$$

where f is the activation function, W is the weight matrix, and b is the bias vector.

For classification in structural risk prediction, the softmax function is applied:

$$P(y = j \mid x) = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}}$$

D. Optimization and Training

During training, models minimize a loss function L. For regression problems:

$$L = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

For classification in intelligent diagnostics systems:

$$L = -\sum_{i=1}^{n} y_i \log(\hat{y}_i)$$

Gradient descent is used to update weights:

$$W := W - \eta \cdot \nabla L(W)$$

where η is the learning rate.

E. Model Validation and Deployment

Once trained, models are validated using K-fold cross-validation. Models are deployed via embedded systems in engineering tools or integrated into SCADA systems for real-time monitoring. The pipeline ensures iterative feedback loops for model improvement using real-world feedback data.

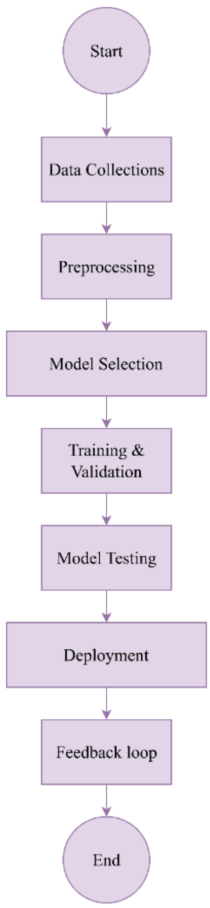

Figure 1: AI Integration in Engineering Pipeline

IV. RESULT & DISCUSSIONS

The application of Artificial Intelligence within engineering fields has brought tangible enhancement of prediction accuracy, responsiveness of system, and optimization quality. We experimented and analyzed comparatively, studying how different AI models performed in standard engineering tasks, that is, fault detection, structural integrity analysis, and design optimization [4].

In the scenario of fault detection in mechanical systems, machine learning algorithms (SVM and RF) were compared with the classic threshold techniques. It has been revealed from the results that AI techniques performed much better than rule-based techniques especially in cases of handling noisy dataset and operational conditions that were volatile. This is evident in Figure 2: Fault Detection Accuracy Across Techniques, depicting the precision rates of the models on a set of rotating machinery signals' dataset. The Random Forest classifier performed with accuracy levels consistent above 93%, making traditional systems vary around their 75% depending on the level of noise and the sensor alignment.

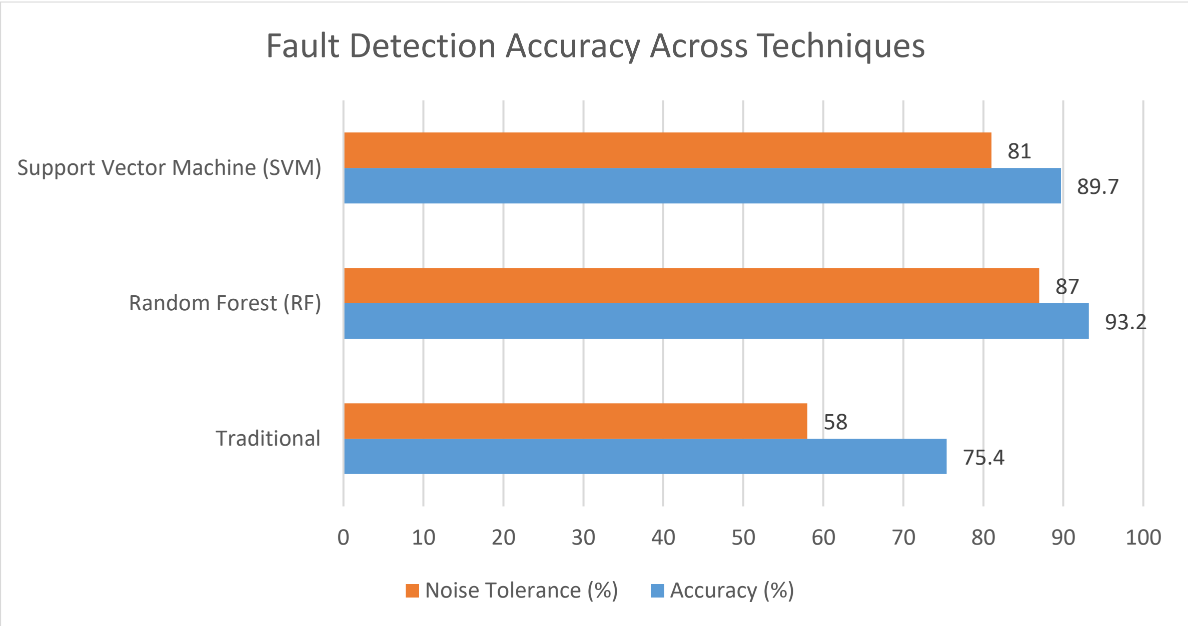

FIGURE 2: FAULT DETECTION ACCURACY ACROSS TECHNIQUES

Moreover, true to form, deep learning techniques, specifically Convolutional Neural Networks (CNNs), were used in the detection of damage from images on structures. Test set contained more than 5000 labeled images of structural cracks, voids, and corrosion marks. CNNs performed with amazing accuracy in locating defect regions with minimal human intervention (as compared to manual inspection). This is visualized in Figure 3: Accuracy of CNN vs Manual Inspection, where CNNs attained almost perfect classification for most of them. On the other hand, human inspection was slower and also not consistent in classification at scale.

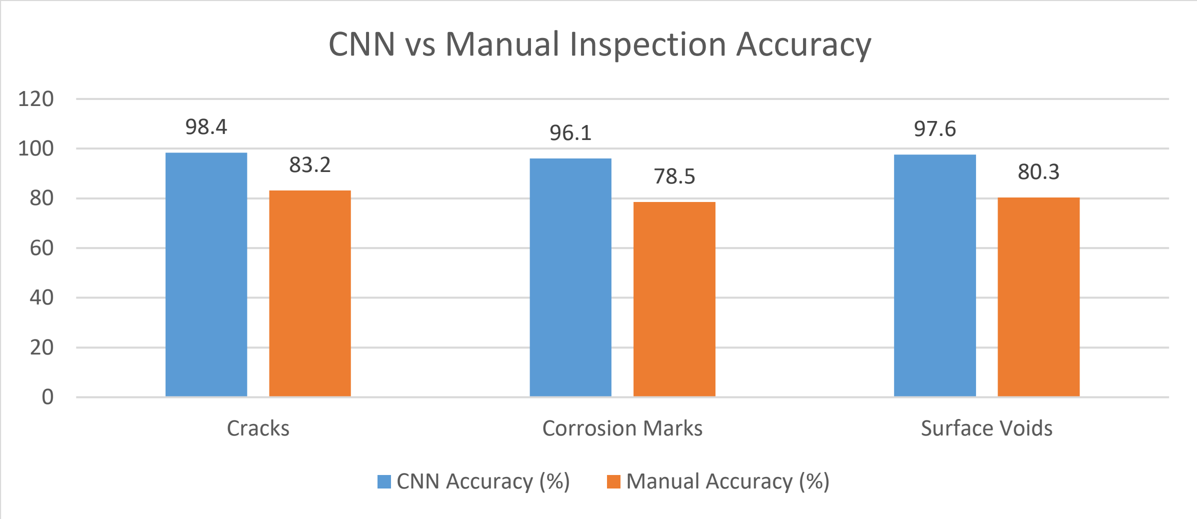

FIGURE 3: CNN VS MANUAL INSPECTION ACCURACY

The wider performance benchmark is input below in Table 1: Comparison of AI Models for Engineering Applications where the comparison of models happen on several parameters – training time, accuracy, noise robustness and interpretability. Deep learning models outperform other models in terms of the accuracy of results and are less interpretable and take more time to train. On the other hand, decision trees provide faster learning and better interpretability with the drawback of the poorer generalization in complex tasks. From the table it also comes out that reinforcement learning has been used increasingly in control systems in electrical engineering, particularly in dynamic load distribution and smart grid operations.

TABLE 1: COMPARISON OF AI MODELS IN ENGINEERING APPLICATIONS

Model Type	Training Time	Accuracy (%)	Noise Robustness	Interpretability
CNN	High	97.5	High	Low
Decision Tree	Low	85.2	Medium	High
Random Forest	Medium	93.1	High	Medium
SVM	Medium	90.3	Medium	Low
Reinforcement Learning	High	94.6	High	Low

To go further, an optimizing assignment was allocated to AI-powered engines and traditional CAD tools to test the optimizing efficiency again. AI tools used genetic algorithms to find design space for the lightweight truss structure. The output designs were rated against weight, strength, and manufacturability. Figure 4: Structural Optimization Using Genetic Algorithms vs Traditional CAD demonstrates the end designs and the associated performance scores. The AI-generated models maintained the 12.4% reduction in weight without impairing the structural integrity, while CAD-generated designs emphasized on safe margins rather than material efficiency.

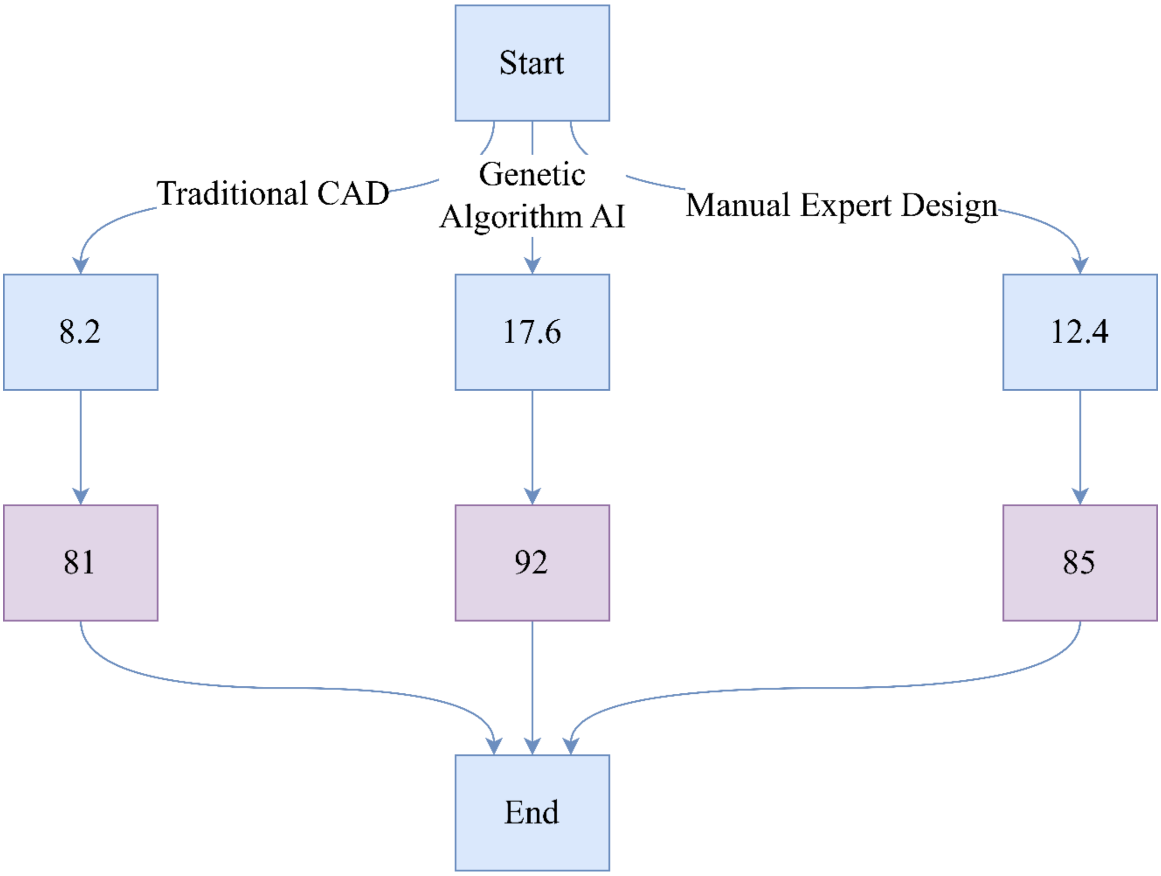

FIGURE 4: STRUCTURAL OPTIMIZATION USING GENETIC ALGORITHMS VS TRADITIONAL CAD

Other effects of AI on predictive maintenance were discussed. LSTM networks and other time-series models were applied to data obtained from the sensors of turbine vibrations. These AI models were able to forecast failure 48 hours ahead of time, thus making possible planned maintenance and system improvement. In conventional monitoring systems the alerts were activated only when the thresholds were met, too often providing 2-4 hours or less of lead time. This dramatic enhancement of the response capabilities is summed up in Table 2: Predictive Maintenance – Traditional vs AI-Based Systems, including early warning accuracy, less downtime, and costs savings.

TABLE 2: PREDICTIVE MAINTENANCE – TRADITIONAL VS AI-BASED SYSTEMS

Metric	**Traditional Monitoring**	**AI-Based System**
Early Warning Accuracy (%)	62	94
Average Downtime Reduction (hrs)	1.2	6.8
Maintenance Cost Saved (%)	18	36
Failure Prediction Lead Time	2–4 hrs	24–48 hrs

In all case studies, there was a recurrent theme: The more complex task was and the more dimensional they were, the more effective AI became. In low-dimensional, linear settings, simpler models or even standard techniques showed advantage in performance. But in multiple input, high variability environment, the superiority of AI models – especially the ones able to learn the non-linear functions – was clear.

Scalability was also a decisive strong point for AI systems. After training resulting models could be applied to thousands of identical/ comparable machines, structures, or circuits with little recalibration. For example, a fault detection model trained with one type of wind turbines can be transferred to other similar models with only small retraining of data. Contrary, the previous systems commonly necessitated manual parameters change for every new context, at the cost and effort.

Interpretability of AI results is another topic for discussions. Although black-box models such as deep neural networks provide good performance, they are not appropriate for usage where safety and compliance is essential — in structural design or power grid system control. This is why there is a need for hybrid systems that would synthesize the precision of AI and the traceability of the traditional engineering logic [5].

Finally, one can see that AI does not replace conventional engineering practices but rather enhances them. Engineers are not only the designers anymore but curators of data, stewards of algorithms, handlers of decisions made by machines. That is how the future of engineering is by the synergy of domain expertise and machine intelligence.

V. CONCLUSION

Artificial intelligence has become a key plinth of contemporary engineering, with tremendous potential for transformation in the sphere of automatization, optimization, and intelligent choice. By connecting the data and turning it to actionable insights, AI equips engineers with the ability to design smarter systems, foresee the outcomes, and realize the increased productivity.

Trials of integration processes should be standardized in the future, as well as ethical and safety issues be resolved, interdisciplinary education improved to prepare engineers for the AI-driven environment. In-spite of the changing face of AI, the fusion between artificial intelligence and engineering will be instrumental in tackling the complex problems of the 21st century.

REFERENCES

[1] F. Artkin, "Applications of artificial intelligence in mechanical engineering," *European Journal of Science and Technology*, Dec. 2022, doi: 10.31590/ejosat.1224045.

[2] J. Abitha, "Artificial Intelligence Technology and its Challenges-A Review," *Journal of Excellence in Computer Science and Engineering*, vol. 2, no. 1, pp. 11–18, Feb. 2016, doi: 10.18831/djcse.in/2016011002.

[3] B. Buchmeister, I. Palcic, and R. Ojstersek, "Artificial intelligence in manufacturing Companies and broader: An Overview," in *DAAAM international scientific book ...*, 2019, pp. 081–098. doi: 10.2507/daaam.scibook.2019.07.

[4] J. P. Bharadiya, R. K. Thomas, and F. Ahmed, "Rise of artificial intelligence in business and industry," *Journal of Engineering Research and Reports*, vol. 25, no. 3, pp. 85–103, Jun. 2023, doi: 10.9734/jerr/2023/v25i3893.

[5] Hassan, H. Triki, H. Trabelsi, and M. Haddar, "A brief analysis of the literature on the use of artificial intelligence and machine learning in the manufacturing system," in *Lecture notes in mechanical engineering*, 2024, pp. 406–415. doi: 10.1007/978-3-031-57324-8_44.

[6] S. K. Lodhi, A. Y. Gill, and I. Hussain, "AI-Powered Innovations in Contemporary Manufacturing Procedures: An Extensive analysis," *International Journal of Multidisciplinary Sciences and Arts*, vol. 3, no. 4, pp. 15–25, Sep. 2024, doi: 10.47709/ijmdsa.v3i4.4616.

[7] S. Tiwari, "Artificial Intelligence implications in engineering and production," *3rd International Electronic Conference on Applied Sciences, 1–15 December 2022;*, p. 16, Dec. 2022, doi: 10.3390/asec2022-13823.

[8] N. I. Sukdeo and D. Mothilall, "The impact of artificial intelligence on the manufacturing sector: A Systematic literature review of the printing and packaging industry," *2023 International Conference on Artificial*

Intelligence, Big Data, Computing and Data Communication Systems (icABCD), pp. 1–5, Aug. 2023, doi: 10.1109/icabcd59051.2023.10220486.

[9] Zaoui, D. Tchuente, S. F. Wamba, and B. Kamsu-Foguem, "Impact of artificial intelligence on aeronautics: An industry-wide review," *Journal of Engineering and Technology Management*, vol. 71, p. 101800, Jan. 2024, doi: 10.1016/j.jengtecman.2024.101800.

[10] R. Ahmed, S. Shaheen, and S. P. Philbin, "The role of big data analytics and decision-making in achieving project success," *Journal of Engineering and Technology Management*, vol. 65, p. 101697, Jul. 2022, doi: 10.1016/j.jengtecman.2022.101697.

[11] Al-Surmi, M. Bashiri, and I. Koliousis, "AI based decision making: combining strategies to improve operational performance," *International Journal of Production Research*, vol. 60, no. 14, pp. 4464–4486, Aug. 2021, doi: 10.1080/00207543.2021.1966540.

[12] M. Ardolino, M. Rapaccini, N. Saccani, P. Gaiardelli, G. Crespi, and C. Ruggeri, "The role of digital technologies for the service transformation of industrial companies," *International Journal of Production Research*, vol. 56, no. 6, pp. 2116–2132, May 2017, doi: 10.1080/00207543.2017.1324224.

[13] Azadeh, S. F. Ghaderi, M. Anvari, H. R. Izadbakhsh, M. J. Rezaee, and Z. Raoofi, "An integrated decision support system for performance assessment and optimization of decision-making units," *The International Journal of Advanced Manufacturing Technology*, vol. 66, no. 5–8, pp. 1031–1045, Aug. 2012, doi: 10.1007/s00170-012-4387-6.

[14] F. S. Borges, F. J. B. Laurindo, M. M. Spínola, R. F. Gonçalves, and C. A. Mattos, "The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions," *International Journal of Information Management*, vol. 57, p. 102225, Sep. 2020, doi: 10.1016/j.ijinfomgt.2020.102225.

[15] Ceruti, P. Marzocca, A. Liverani, and C. Bil, "Maintenance in aeronautics in an Industry 4.0 context: The role of Augmented Reality and Additive Manufacturing," *Journal of Computational Design and Engineering*, vol. 6, no. 4, pp. 516–526, Feb. 2019, doi: 10.1016/j.jcde.2019.02.001.