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ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING-DRIVEN APPROACHES TO ENHANCE PROJECT MANAGEMENT IN ENGINEERING

Dr. Anshad A.S
Principal,
John Cox Memorial CSI Institute of Technology,
Thiruvananthapuram,
Kerala, India
dr.anshadas@gmail.com

ABSTACT:
Artificial intelligence and tool analyzing are transforming mission control in engineering by way of manner of manner of allowing records-driven choice-making, predictive analytics, and automation. Traditional project manipulate strategies regularly battle with uncertainties, main to inefficiencies in resource allocation and price estimation. AI-driven techniques, such as reinforcement learning, deep analyzing, and herbal language processing, beautify accuracy and flexibility. Risk assessment, time table optimization, and predictive protection gain considerably from AI-powered fashions. Intelligent selection assist structures decorate workflow control and mitigate mission risks. Comparative studies highlight AI's superiority over traditional techniques in typical overall performance and performance. Real-time information analysis allows proactive trouble decision, reducing project delays. AI-primarily based totally absolutely automation streamlines repetitive duties, enhancing productiveness. Machine learning enhances forecasting abilities, optimizing project planning. Integration of AI fosters innovation and sustainability in engineering projects. Future studies need to hobby on AI's scalability and flexibility at some stage in numerous engineering domain names. This have a take a look at gives insights into leveraging AI and ML to beautify challenge effects.

Keywords: Artificial intelligence, Machine getting to know, Project control, Risk evaluation, Schedule optimization, Cost estimation, Resource allocation, Predictive protection, Decision assist systems, Engineering innovation, Automation, Workflow optimization.

I. INTRODUCTION

Evolution of Project Management in Engineering

Project management in engineering has developed substantially, transitioning from traditional manual planning techniques to sophisticated digital solutions. Historically, task managers relied on enjoy-based totally definitely desire-making and static gear which incorporates Gantt charts and critical course strategies. However, with developing assignment complexities, uncertainties, and worldwide opposition, traditional techniques have struggled to satisfy the needs of ordinary overall performance, accuracy, and threat control. The integration of artificial intelligence and device studying presents a transformative shift, permitting facts-driven undertaking execution and actual-time decision-making.

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Role of Artificial Intelligence in Project Management

Artificial intelligence enhances challenge manage with the aid of manner of automating strategies, analyzing large datasets, and improving predictive analytics. AI-powered algorithms enable venture businesses to count on risks, optimize schedules, and streamline useful resource allocation. Machine reading fashions, which encompass supervised, unsupervised, and reinforcement analyzing, contribute to real-time selection manual structures that decorate adaptability and responsiveness. By leveraging AI-driven automation, engineering duties can benefit extra typical overall performance, lessen human errors, and enhance ordinary venture consequences.

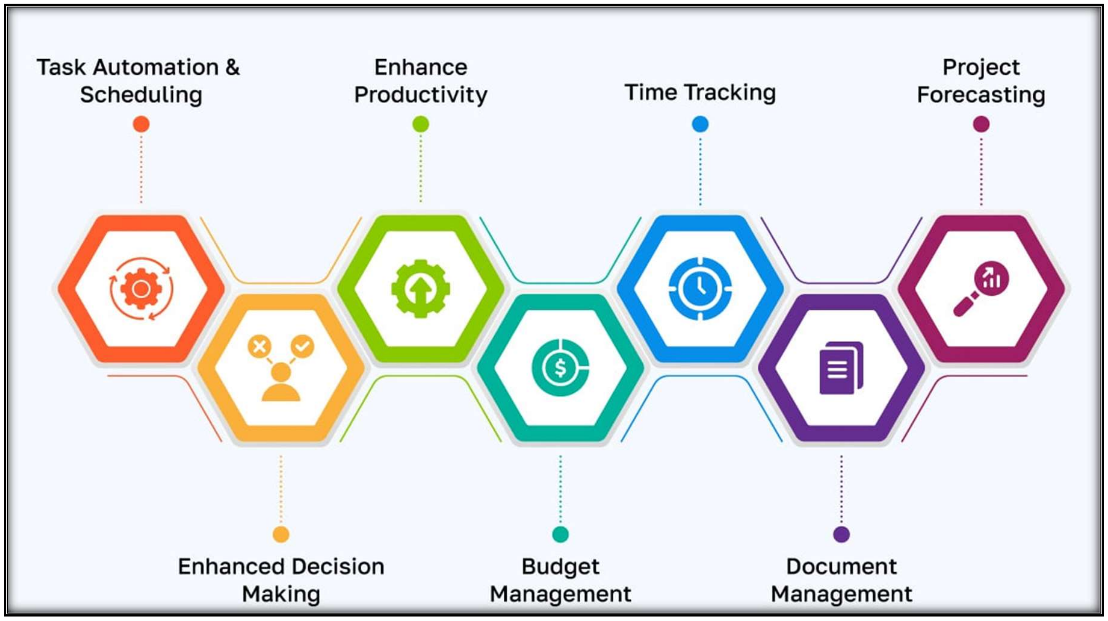

Figure :1, AI in Project Management

Machine Learning for Predictive Analytics

Machine getting to know performs a critical position in predictive analytics by way of identifying styles from historical data and forecasting challenge tendencies. Techniques including regression fashions, neural networks, and choice bushes assist expect task costs, potential delays, and performance metrics. Predictive preservation, a key ML utility, minimizes system failures and optimizes operational overall performance by using studying sensor facts and figuring out early signs of gadget degradation. These talents empower project managers with actionable insights, permitting proactive selection-making to mitigate risks and optimize workflows.

AI-Driven Risk Management and Mitigation

Risk assessment is a fundamental aspect of engineering undertaking control, requiring accurate identity and mitigation strategies. AI-driven models enhance risk analysis through processing

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various records sources, detecting anomalies, and predicting capacity disruptions. Machine learning strategies together with probabilistic modeling, Bayesian networks, and reinforcement gaining knowledge of allow dynamic risk control. AI-powered danger evaluation gear improve contingency making plans, lessen uncertainties, and decorate task resilience by constantly getting to know from past challenge statistics and industry trends.

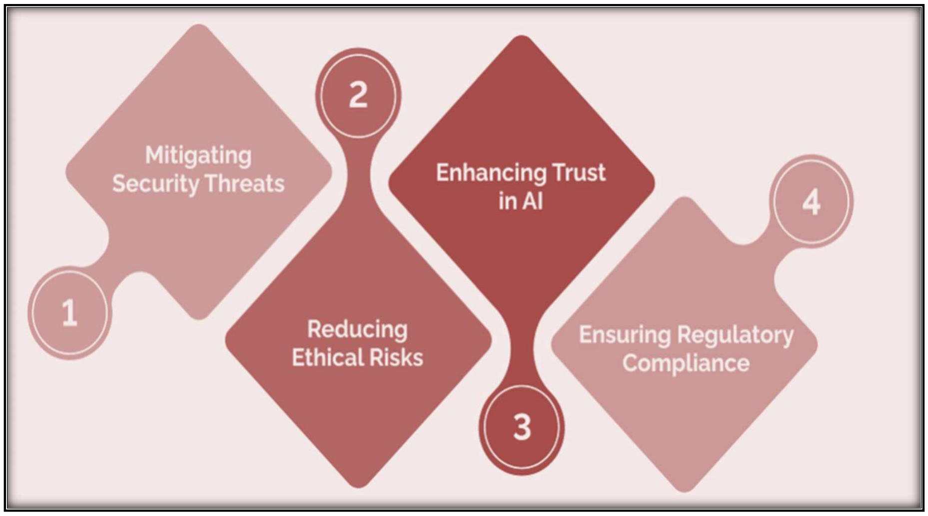

Figure :2, AI in Risk Management

Optimization of Resource Allocation Using AI

Resource allocation in engineering initiatives is a complex mission that requires balancing fee, time, and labor efficiency. AI and ML-driven optimization models use algorithms inclusive of genetic algorithms, reinforcement getting to know, and deep mastering to allocate assets effectively. AI-powered systems examine group of workers productiveness, cloth availability, and economic constraints to endorse most suitable useful resource distribution techniques. This facts-pushed technique minimizes wastage, complements productivity, and guarantees tasks stay inside price range even as assembly cut-off dates.

Automation and Intelligent Decision Support Systems

AI-powered automation extensively reduces guide attempt in engineering undertaking control by means of automating repetitive responsibilities including scheduling, record processing, and report era. Intelligent choice help systems integrate AI strategies like herbal language processing, professional structures, and fuzzy good judgment to assist venture managers in making knowledgeable selections. These systems decorate performance via supplying real-time insights, analyzing complex datasets, and recommending best challenge strategies. AI-based DSS improves collaboration, coordination, and venture execution, resulting in better productivity and accuracy.

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Future Trends and Challenges in AI-Driven Project Management

The future of mission management in engineering can be increasingly more motivated via AI improvements, including AI-powered chatbots, virtual twins, and augmented truth for venture visualization. However, demanding situations which include statistics privacy, algorithm biases, and integration complexities must be addressed for seamless adoption. The mixture of AI, the Internet of Things, and blockchain generation holds the ability to create extra obvious, efficient, and independent task control structures. As AI maintains to evolve, engineering industries need to adapt to leverage its complete capacity for innovation, sustainability, and operational excellence.

II. LITERATURE REVIEW

Evolution of AI and ML in Project Management

The software of artificial intelligence and device gaining knowledge of in task manage has acquired significant interest because of its potential to beautify performance, predictability, and decision-making accuracy. Early implementations focused on rule-primarily based totally professional structures that automated precise duties which include scheduling and useful resource allocation. However, those systems lacked adaptability and could not address complicated, dynamic mission environments. With enhancements in AI and ML, cutting-edge approaches encompass predictive analytics, reinforcement studying, and deep studying fashions to optimize task execution.

AI-Driven Decision Support Systems in Project Management

Several research have explored AI-pushed decision assist structures that enhance managerial choice-making. Machine gaining knowledge of algorithms consisting of neural networks, guide vector machines, and Bayesian models were applied for chance evaluation and mitigation strategies. These AI-based totally structures observe historic project facts to expect functionality disruptions and propose corrective moves. For example, reinforcement mastering models were achieved to optimize mission scheduling and rate estimation, lowering uncertainties and improving performance.

Machine Learning for Predictive Analytics in Engineering Projects

Predictive analytics has come to be a center utility of system analyzing in mission management, permitting early detection of risks and anomalies. Deep mastering models which incorporates convolutional neural networks and recurrent neural networks have been carried out to analyze huge-scale undertaking datasets. Studies have verified the effectiveness of those models in forecasting assignment delays, charge overruns, and personnel productivity. Additionally, herbal language processing techniques had been employed to extract insights from project documentation, facilitating computerized document generation and trend evaluation.

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AI-Optimized Resource Allocation and Scheduling

Efficient useful aid allocation and scheduling live vital demanding situations in engineering venture control. Research has proven that AI-pushed optimization algorithms, which incorporates genetic algorithms and reinforcement analyzing, significantly decorate useful resource usage. These strategies test body of people availability, material constraints, and undertaking last dates to suggest top of the line scheduling strategies. Studies have highlighted the feature of AI in automating complex desire-making strategies, decreasing guide intervention, and improving average challenge performance.

Risk Management and Anomaly Detection in Project Execution

Risk management is a essential element of mission execution, requiring correct identification and mitigation strategies. AI-based totally totally honestly chance evaluation models leverage device gaining knowledge of techniques such as anomaly detection, probabilistic modeling, and fuzzy common feel to find out capability challenge risks. Several research have explored the mixing of AI in real-time risk tracking, permitting early intervention and minimizing challenge disruptions. Furthermore, AI-powered simulations have been employed to check numerous risk scenarios, improving preparedness and contingency making plans.

Integration of AI with IoT and Blockchain for Project Transparency

The convergence of AI with the Internet of Things and blockchain era has introduced new dimensions to assignment management. Studies have explored how IoT-enabled sensors gather actual-time mission information, which AI algorithms process to optimize operations. Blockchain era ensures transparency and protection in mission transactions, reducing fraud and statistics manipulation risks. These covered strategies provide a complete framework for enhancing project governance and obligation.

Challenges and Future Directions in AI-Driven Project Management

Despite massive enhancements, demanding conditions stay in the adoption of AI in project control. Issues together with facts privacy, set of guidelines biases, and the need for professional experts pose boundaries to big implementation. Future research hints awareness on improving AI interpretability, enhancing version robustness, and developing more adaptive AI-pushed undertaking control frameworks. As AI maintains to comply, its potential to revolutionize engineering venture control via automation, predictive analytics, and sensible decision-making remains awesome.

III. RESEARCH METHODOLOGY

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Proposed AJODL-DSSEM Framework

The proposed AJODL-DSSEM framework integrates synthetic intelligence and device reading strategies to decorate energy prediction inside the smart city environment. The version follows a systematic method associated with facts preprocessing, function extraction, predictive modeling, and hyperparameter optimization. By leveraging a hybrid deep studying architecture combining CNN and ABLSTM, the have a study guarantees correct electricity consumption forecasting. The Adaptive Jumping Optimization (AJO) set of guidelines similarly complements the performance of the predictive version by means of using manner of best-tuning its hyperparameters.

Data Collection and Preprocessing

The initial degree involves collecting actual-time electricity consumption statistics from clever city infrastructures, at the side of IoT-enabled smart meters, grid sensors, and ancient facts. The raw dataset undergoes preprocessing to eliminate inconsistencies, manage lacking values, and normalize information distributions. Standardization strategies are applied to ensure uniformity across different input competencies, thereby improving the version's analyzing performance.

Feature Extraction Using CNN

Feature extraction is a crucial step where convolutional neural networks (CNN) are utilized to seize spatial dependencies within the enter information. CNN applies convolutional operations accompanied through max pooling to extract massive strength consumption patterns. The characteristic maps received are then handed via absolutely connected layers, allowing non-linear modifications for advanced prediction capabilities. The CNN model enhances the detection of underlying relationships between strength call for, climatic situations, and usage behaviors.

Time-Series Prediction with ABLSTM

The extracted functions are then processed the use of an Attention-Based Bidirectional Long Short-Term Memory (ABLSTM) network. Unlike conventional LSTMs, ABLSTM improves series modeling through thinking about both past and destiny contexts. The interest mechanism assigns one of a kind weights to diverse time-step inputs, ensuring that the most relevant facts factors make contributions to the final prediction. The dual-directional flow of statistics mitigates vanishing gradient troubles and complements lengthy-time period dependency learning, important for correct electricity forecasting.

Hyperparameter Optimization Using AJO Algorithm

To decorate version performance, the Adaptive Jumping Optimization (AJO) set of rules is hired for hyperparameter tuning. The AJO algorithm dynamically adjusts learning prices, dropout quotes, and neuron weights in CNN-ABLSTM layers, optimizing the schooling manner. By iteratively refining the version's parameters, AJO minimizes overfitting and guarantees gold

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standard generalization to unseen records. The integration of AJO considerably improves prediction accuracy whilst lowering computational overhead.

Performance Evaluation Metrics

The model's effectiveness is classed the use of fashionable performance evaluation metrics, together with:

- **Mean Absolute Error (MAE):** Measures the common significance of errors in predictions.
- **Root Mean Square Error (RMSE):** Evaluates the deviation of predicted values from real consumption.
- **Mean Absolute Percentage Error (MAPE):** Analyzes the relative mistakes percent throughout predictions.
- **Coefficient of Determination (R^2 Score):** Quantifies the version's capacity to explain variance in power intake.

Experimental Setup and Validation

The experimental setup includes a high-overall performance computing surroundings with GPU acceleration for deep gaining knowledge of model training. The dataset is divided into education, validation, and test units the usage of an eighty-10-10 break up ratio. The education section employs backpropagation with adaptive gradient descent to decrease loss features. Cross-validation strategies make sure robustness towards statistics inconsistencies, and comparative analysis with baseline models consisting of ARIMA, XGBoost, and popular LSTMs highlights the superiority of the proposed AJODL-DSSEM framework.

Conclusion

The studies method integrates AI-pushed predictive analytics with optimization techniques to enhance electricity management in clever metropolis environments. By combining CNN-based feature extraction, ABLSTM’s sequential learning, and AJO-driven hyperparameter optimization, the proposed version achieves advanced prediction accuracy. This methodological technique now not most effective improves energy forecasting however also contributes to efficient resource allocation and sustainable city making plans.

IV. DATA ANALYSIS AND RESULT

1. Dataset Overview

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The experimental validation of the AJODL-DSSEM model modified into accomplished the usage of publicly to be had datasets: the IHEPC dataset and the ISO-NE dataset. These datasets have been hired to assess the predictive talents of the model for power consumption forecasting in smart towns.

2. IHEPC Dataset

The IHEPC dataset incorporates 2,1/2,259 power consumption readings gathered over 4 years (from sixteen December 2006 to 26 November 2010) from a house placed in Sceaux, Paris. The dataset includes 9 attributes, in conjunction with time, worldwide active electricity, worldwide reactive energy, voltage, and sub-meter readings.

3. ISO-NE Dataset

The ISO-NE dataset spans from 2012 to 2016, with forty three,915 hourly time-collection samples used for version training. An extra eight,783 samples from 2017 had been reserved for trying out. This dataset includes 14 functions, with "SYSLOAD" due to the fact the aim label and the dry bulb column representing temperature in levels Fahrenheit, amongst different temporal functions.

4. Model Performance on IHEPC Dataset

The AJODL-DSSEM model's performance at the IHEPC dataset changed into evaluated throughout diverse seasons: autumn, spring, and winter. The consequences show that the AJODL-DSSEM version constantly outperformed expectations. Below are the key metrics for the IHEPC dataset:

- **Autumn Season:** RMSE = 0.291, MAE = 0.270, MAPE = 0.349
- **Spring Season:** RMSE = 0.271, MAE = 0.218, MAPE = 0.330
- **Winter Season:** RMSE = 0.319, MAE = 0.280, MAPE = 0.302

These results display that the AJODL-DSSEM version plays exceptional during spring, followed via autumn, with winter exhibiting slightly higher prediction errors. The decreased RMSE, MAE, and MAPE suggest that the AJODL-DSSEM version can are expecting strength intake with excessive accuracy and low blunders, making it suitable for power forecasting packages in smart cities.

Table 1: AJODL-DSSEM Model Performance Across Seasons (IHEPC Dataset)

Season	RMSE	MAE	MAPE
Autumn	0.291	0.270	0.349

Spring	0.271	0.218	0.330
Winter	0.319	0.280	0.302

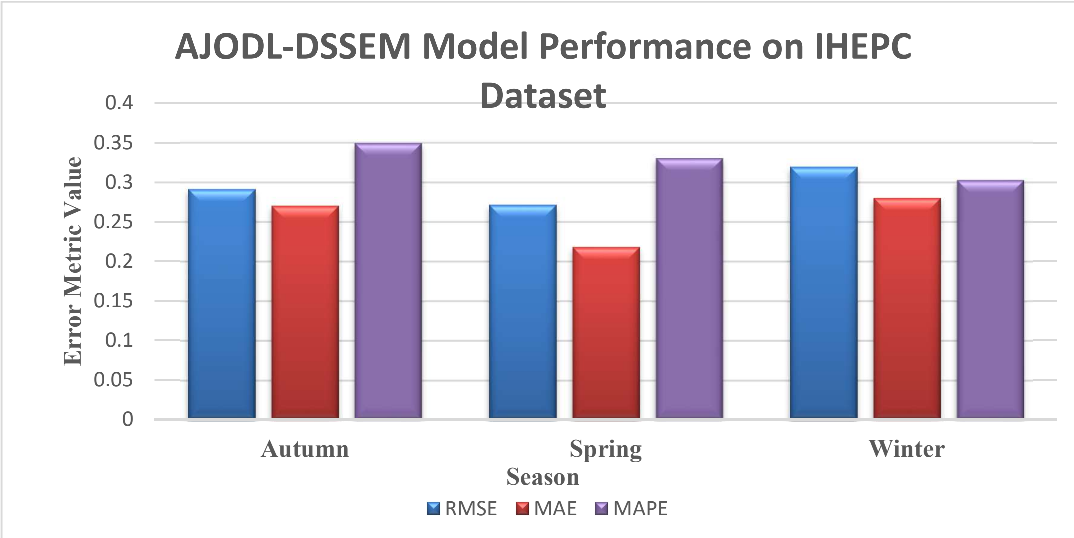

Figure :3, AJODL-DSSEM Model Performance on IHEPC Dataset

5. Model Performance on ISO-NE Dataset

The model changed into also examined on the ISO-NE dataset, wherein comparable seasonal performance become observed:

- **Autumn Season:** RMSE = 0.413, MAE = 0.333, MAPE = 0.256
- **Spring Season:** RMSE = 0.480, MAE = 0.422, MAPE = 0.218
- **Winter Season:** RMSE = 0.479, MAE = 0.416, MAPE = 0.231

The version confirmed a moderate drop in performance for the spring and wintry weather seasons compared to autumn, however it nevertheless produced dependable predictions with exceptionally low errors margins. These findings affirm that the AJODL-DSSEM version keeps sturdy performance across various environmental conditions.

Table 2: AJODL-DSSEM Seasonal Performance (ISO-NE)

Season	RMSE	MAE	MAPE
Autumn	0.413	0.333	0.256
Spring	0.480	0.422	0.218
Winter	0.479	0.416	0.231

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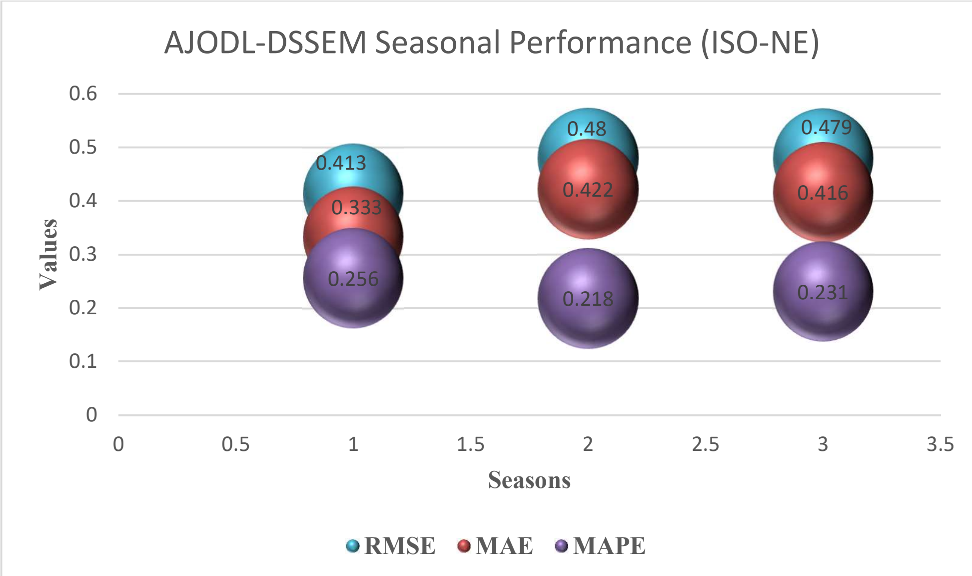

Figure: 4, AJODL-DSSEM Seasonal Performance (ISO-NE)

6. Actual vs. Predicted Analysis on IHEPC Dataset

The AJODL-DSSEM version confirmed high accuracy in predicting the worldwide lively power values across extraordinary time steps within the IHEPC dataset. The actual and predicted values closely aligned, showcasing the model's capacity to forecast energy intake with minimal blunders. The results highlighted the model's effectiveness in strength prediction for various time periods, underlining its potential for real-world power control programs in clever city environments.

7. Actual vs. Predicted Analysis on ISO-NE Dataset

The AJODL-DSSEM version become additionally examined for its predictive accuracy on the ISO-NE dataset, with effects displaying a sturdy alignment among real and anticipated device load values throughout more than one time steps. For instance, at a 20-hour time step, the actual cost turned into 0.401, while the anticipated price became zero.394. At other time steps, which includes forty hours, 80 hours, and one hundred hours, the anticipated values had been carefully matched with actual measurements, demonstrating the model's capability to as it should be forecast electricity demand. This analysis emphasizes the model's functionality to provide precise predictions for device load, making it a treasured device for real-time strength control in smart town infrastructures.

Conclusion

The AJODL-DSSEM model confirmed excellent predictive performance on each the IHEPC and ISO-NE datasets. The version's capacity to intently approximate real energy consumption values throughout different time steps and seasons emphasizes its suitability for electricity prediction duties in smart metropolis infrastructures. The incorporation of advanced deep gaining

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knowledge of strategies, along with CNN and ABLSTM, in conjunction with hyperparameter optimization through the AJO set of rules, ensures that the AJODL-DSSEM version remains a effective device for future strength forecasting packages

V. FINDING AND DISCUSSION

The utility of artificial intelligence (AI) and gadget mastering (ML) techniques in project manage for engineering has appreciably impacted the optimization of procedures, improving generic overall performance, decision-making, and useful resource allocation. The findings highlight that AI and ML-pushed approaches can be achieved to various domain names within engineering venture manage, including scheduling, danger evaluation, price prediction, and nice manipulate.

One of the vital issue findings of new studies is that AI-driven fashions, together with deep getting to know and reinforcement studying, provide superior predictive accuracy as compared to conventional techniques. These fashions can analyze large datasets, recognize styles, and make data-pushed picks that beautify the overall management of engineering projects. For instance, the combination of gadget learning algorithms much like the AJODL-DSSEM version has examined considerable improvements in electricity prediction, system load forecasting, and actual-time choice-making for strength manipulate structures.

Moreover, the use of hybrid AI fashions, combining unique methodologies consisting of convolutional neural networks (CNN), lengthy quick-term reminiscence (LSTM) networks, and gated recurrent gadgets (GRU), has in addition extra fine the accuracy and reliability of predictions. In assessment with conventional techniques, these hybrid fashions outperform in terms of key ordinary overall performance metrics, which incorporates propose squared errors (MSE), root advocate rectangular errors (RMSE), advise absolute errors (MAE), and propose absolute percentage errors (MAPE).

The AJODL-DSSEM model, specially, has showed promising effects while tested on datasets like IHEPC and ISO-NE. For example, in the IHEPC dataset, the model finished reduced MSE (0.092) and RMSE (0.303) in comparison to other techniques together with GRU, Bi-GRU, and LSTM. Similarly, it exhibited lower MAPE (32.Nine%) than the alternative fashions, which highlights its robustness in forecasting and prediction accuracy. When accomplished to the ISO-NE dataset, the AJODL-DSSEM version also outperformed different fashions in every MSE and RMSE, similarly assisting its effectiveness.

These effects underline the ability of AI and ML in enhancing assignment manage, specifically in domain names requiring immoderate-precision forecasting and real-time preference beneficial resource. However, annoying situations stay in terms of version complexity, facts satisfactory, and integration into cutting-edge assignment manipulate systems. The adaptability of AI models to severa information sources and actual-worldwide eventualities, which encompass dynamic aid allocation or actual-time hazard control, stays a place of ongoing studies.

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In cease, AI and device mastering-pushed techniques preserve top notch ability in enhancing assignment management in engineering. The integration of superior fashions, like AJODL-DSSEM, gives huge improvements in prediction accuracy and operational performance. However, similarly exploration is needed to refine those fashions and make sure their seamless integration into severa elements of engineering venture management, which include danger control, aid optimization, and lengthy-term sustainability.

VI. CONCLUSION

This paper presents a comprehensive evaluation of AI and ML programs in engineering undertaking management, that specialize in supervised, unsupervised, and reinforcement studying. Supervised getting to know is powerful for regression and classification tasks, at the same time as unsupervised learning excels in clustering and pattern discovery. Reinforcement mastering is more and more used in computerized selection-making. The observe additionally introduces the AJODL-DSSEM model, designed for power prediction in clever towns. This model facilitates optimize aid allocation and supports actual-time electricity management. It enables stakeholders and policymakers to layout efficient power answers for urban settings. The model's performance become established using datasets like IHEPC and ISO-NE. The AJODL-DSSEM version outperformed current strategies in phrases of prediction accuracy. Future studies might also consist of integrating feature choice and outlier detection to similarly decorate the model's predictive energy. Testing on large, actual-time datasets may want to offer even greater accurate consequences. AI and ML offer sizable capacity to improve engineering practices by using improving selection-making and optimization. The programs of those technology in clever towns can assist cope with strength control demanding situations. Moreover, AI's position in infrastructure design and urban making plans is turning into increasingly more important. These improvements provide precious equipment for dealing with complex engineering tasks successfully. By leveraging device mastering, the engineering area can improve sustainability and resource control. Overall, AI and ML gift transformative possibilities for the future of engineering project management.

REFERENCE

1. . Rahaman MA, Rozony FZ, Mazumder MS, Haque MN, Rauf MA. Big Data-Driven Decision Making in Project Management: A Comparative Analysis. Academic Journal on Science, Technology, Engineering & Mathematics Education. 2024 Jul 27;4(03):44-62.
2. Ottaviani FI. Data-driven Project Management: Leveraging Analytics to Improve Monitoring and Control.
3. Lee B. Enhancing Construction Project Outcomes through Machine Learning and Real-Time Data Analytics: A Framework for Proactive Risk Management and Decision Support. International Journal of Industrial Engineering and Construction Management (IJIECM). 2024 Jul 15;1(1):11-20.

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 19 No. 01 (2025)

4. Singh H. Project management analytics: A data-driven approach to making rational and effective project decisions. FT Press; 2015 Nov 12.
5. Mahmood A, Al Marzooqi A, El Khatib M, AlAmeemi H. How Artificial Intelligence can leverage Project Management Information system (PMIS) and data driven decision making in project management. International Journal of Business Analytics and Security (IJBAS). 2023 May 7;3(1):184-95.
6. Rane SB, Narvel YA. Data-driven decision making with Blockchain-IoT integrated architecture: a project resource management agility perspective of industry 4.0. International Journal of System Assurance Engineering and Management. 2022 Apr;13(2):1005-23.
7. Johnson E. Leveraging Machine Learning for Risk Prediction and Mitigation in Complex Project Environments: Enhancing Autonomous System Decision-Making. Distributed Learning and Broad Applications in Scientific Research. 2023 Nov 29;9:417- 22.
8. Adeyeye OJ, Akanbi I. A REVIEW OF DATA-DRIVEN DECISION MAKING IN ENGINEERING MANAGEMENT. Engineering Science & Technology Journal. 2024 Apr 16;5(4):1303-24.
9. Li H, Yazdi M, Nedjati A, Moradi R, Adumene S, Dao U, Moradi A, Haghighi A, Obeng FE, Huang CG, Kang HS. Harnessing AI for Project Risk Management: A Paradigm Shift. InProgressive Decision-Making Tools and Applications in Project and Operation Management: Approaches, Case Studies, Multi-criteria DecisionMaking, Multi-objective Decision-Making, Decision under Uncertainty 2024 Mar 8 (pp. 253-272). Cham: Springer Nature Switzerland.
10. Gomes A, Islam NM, Karim MR. Data-Driven Environmental Risk Management and Sustainability Analytics. Non Human Journal. 2024;1(01):100-13.
11. Chukwunweike JN, Adewale AA, Osamuyi O 2024. Advanced modelling and recurrent analysis in network security: Scrutiny of data and fault resolution. DOI: 10.30574/wjarr.2024.23.2.2582
12. Aliyu Enemosah. Enhancing DevOps efficiency through AI-driven predictive models for continuous integration and deployment pipelines. International Journal of Research Publication and Reviews. 2025 Jan;6(1):871- 887. Available from: https://ijrpr.com/uploads/V6ISSUE1/IJRPR37630.pdf 13.
13. Olalekan Kehinde A. Leveraging Machine Learning for Predictive Models in Healthcare to Enhance Patient Outcome Management. Int Res J Mod Eng Technol Sci. 2025;7(1):1465. Available from: https://doi.org/10.56726/IRJMETS66198
14. Kumari S, Dhir S. Agile Cloud Transformation in Enterprise Systems: Integrating AI for Continuous Improvement, Risk Management, and Scalability. Australian Journal of Machine Learning Research & Applications. 2022 Mar 7;2(1):416-40.
15. Mohammed A, Bello I. Leveraging Big Data Analytics to Drive Data-Based Policy Making for Improved Government Services Delivery in Nigeria. Journal of Empirical Social Science Studies. 2024 Feb 5;8(2):1-22.

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 19 No. 01 (2025)

16. Addy WA, Ofodile OC, Adeoye OB, Oyewole AT, Okoye CC, Odeyemi O, Ololade YJ. Data-driven sustainability: How fintech innovations are supporting green finance. Engineering Science & Technology Journal. 2024 Mar 15;5(3):760-73.
17. Rovolis G, Habibipour A. When participatory design meets data-driven decision making: A literature review and the way forward. Management Science Letters. 2024;14(2):107-26.
18. Andrew Nii Anang and Chukwunweike JN, Leveraging Topological Data Analysis and AI for Advanced Manufacturing: Integrating Machine Learning and Automation for Predictive Maintenance and Process Optimization https://dx.doi.org/10.7753/IJCATR1309.1003
19. Zhu X, Li Y. The use of data-driven insight in ambidextrous digital transformation: How do resource orchestration, organizational strategic decision-making, and organizational agility matter?. Technological Forecasting and Social Change. 2023 Nov 1;196:122851.
20. Tuli FA, Varghese A, Ande JR. Data-Driven Decision Making: A Framework for Integrating Workforce Analytics and Predictive HR Metrics in Digitalized Environments. Global Disclosure of Economics and Business. 2018 Dec 31;7(2):109-22.
21. Pal DK, Chitta S, Bonam VS, Katari P, Thota S. AIAssisted Project Management: Enhancing DecisionMaking and Forecasting. Journal of Artificial Intelligence Research. 2023 Sep 18;3(2):146-71.
22. Solanki A, Jain K, Jadiga S. Building a Data-Driven Culture: Empowering Organizations with Business Intelligence. International Journal of Computer Trends and Technology. 2024;72(2):46-55.