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Cognitive Computing In Motion: Investigating Real-Time Learning Models For Enhanced Decision-Making In Mobile Environments

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Abstract
This paper investigates real-time learning models for enhancing decision-making in mobile environments, focusing on cognitive computing applications. The research methodology involves generating a hypothetical dataset to simulate input data, splitting it into training and testing sets, and training a Random Forest classifier. The decision boundary of the model is visualized to understand its decision-making process. Additionally, cognitive computing scores are simulated over time to analyze their temporal evolution, and performance metrics for tabulative, programmable, and cognitive systems are visualized. Results and discussions provide insights into the models' performance and behavior, highlighting their potential for improving decision-making in dynamic mobile contexts. The decision boundary graph illustrates the model's ability to differentiate between classes in a two-dimensional feature space, while cognitive computing score graphs depict trends in cognitive computing advancements over time. The visualizations of performance metrics offer valuable insights into the development and implications of various cognitive computing aspects. Overall, this study contributes to advancing real-time learning models for enhanced decision-making in mobile environments, with implications for diverse applications in cognitive computing.

1. Introduction

The integration of cognitive computing technologies with mobile environments has emerged as a promising avenue for revolutionizing real-time decision-making processes. In recent years, the proliferation of mobile devices and advancements in cognitive computing have catalyzed research efforts aimed at harnessing the potential synergy between these domains to enhance decision-making capabilities in dynamic mobile contexts. This introduction delves into the burgeoning field of cognitive computing in motion, focusing on the exploration of real-time learning models tailored for mobile environments to facilitate adaptive and context-aware decision-making. The landscape of mobile computing has undergone rapid evolution, driven by the ubiquitous presence of smartphones, tablets, and wearable devices. As these devices continue to permeate various aspects of everyday life, the demand for intelligent, context-aware applications capable of making timely and informed decisions has intensified. Traditional approaches to decision-making in mobile environments have often been limited by static algorithms and predefined rulesets, which struggle to adapt to the dynamic nature of mobile contexts. Consequently, there has been a paradigm shift towards leveraging cognitive computing techniques to imbue mobile systems with the ability to learn, reason, and make decisions autonomously in real-time.

The fusion of cognitive computing and mobile environments presents a multifaceted research landscape, encompassing diverse domains such as machine learning, artificial intelligence, human-computer interaction, and mobile computing. Numerous studies have explored the potential of cognitive computing technologies, including machine learning algorithms, neural networks, and deep learning models, to empower mobile devices with sophisticated decision-making capabilities. For instance, research by [1] investigated the application of deep reinforcement learning in mobile environments to optimize resource allocation and

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enhance user experience. Similarly, the work of [2] delved into the development of context-aware decision support systems for mobile healthcare using machine learning techniques, demonstrating significant improvements in patient care and treatment outcomes. Real-time learning models lie at the heart of cognitive computing in motion, serving as the cornerstone for adaptive decision-making in dynamic mobile environments. These models leverage techniques such as online learning, incremental learning, and reinforcement learning to continuously adapt and evolve based on incoming data streams and environmental cues. By dynamically adjusting their decision-making strategies in response to changing contexts, real-time learning models enable mobile systems to navigate uncertain and volatile scenarios effectively. Research by [3] exemplifies this approach, wherein they proposed a real-time learning framework for mobile edge computing that optimizes task scheduling and resource allocation in dynamic network environments, thereby enhancing system performance and user satisfaction.

Despite the significant strides made in advancing real-time learning models for mobile decision-making, several challenges and research gaps persist. These include issues related to data privacy and security, computational resource constraints, interpretability of model decisions, and scalability in large-scale mobile environments. Addressing these challenges requires interdisciplinary collaboration among researchers from computer science, cognitive psychology, mobile computing, and ethics to develop holistic solutions that balance technological innovation with societal impact. In the intersection of cognitive computing and mobile environments holds immense potential for reshaping decision-making processes in real-time. By harnessing the power of real-time learning models, mobile systems can adapt and respond intelligently to dynamic environmental stimuli, thereby facilitating enhanced user experiences and driving innovation across various domains.

This paper investigates the role of real-time learning models in cognitive computing in motion, exploring their applications, challenges, and future directions in the context of mobile decision-making. Through a comprehensive literature survey and empirical analysis, we aim to contribute to the evolving discourse on leveraging cognitive computing for enhanced decision-making in mobile environments. A notable research gap in the domain of cognitive computing in motion pertains to the interpretability and transparency of real-time learning models deployed in mobile environments. While these models exhibit remarkable decision-making capabilities, the lack of interpretability hampers their trustworthiness and acceptance in critical applications. Addressing this gap is essential to ensure user confidence and facilitate broader adoption of cognitive systems in mobile decision-making contexts [4].

2. Research Methodology

The research methodology employed in this study encompasses a multifaceted approach aimed at investigating real-time learning models for enhanced decision-making in mobile environments. Firstly, a hypothetical dataset is generated to simulate the input data for the real-time learning model. This dataset consists of features representing various aspects of the mobile environment, such as sensor readings or contextual information, along with corresponding labels indicating the decision outcomes. The dataset is then split into training and testing sets using the train_test_split function from the scikit-learn library, ensuring a balanced distribution of data for model training and evaluation [5]. Subsequently, a real-time learning model is trained using the training set. In this study, a Random Forest classifier is utilized as an example of a real-time learning model due to its ability to handle complex datasets and adapt to changing conditions in real-time. The model is trained on the training set using the fit method, where it learns to make predictions based on the input features. Once trained, the model is evaluated on the testing set to assess its performance in terms of accuracy using the accuracy score metric from scikit-learn [6].

Furthermore, the decision boundary of the trained real-time learning model is visualized using contour plots to illustrate its decision-making capabilities in a two-dimensional feature space. By plotting the decision boundary, insights into how the model separates different classes in the input space can be gleaned, providing a deeper understanding of its behavior and performance in real-time mobile decision-making scenarios. Additionally, the study incorporates the simulation of cognitive computing scores over time to analyze the temporal evolution of cognitive computing, cognitive systems, and cognitive products. This simulation involves generating hypothetical scores for each category at discrete time intervals and plotting them over time using line plots, allowing for the observation of trends and patterns in cognitive computing advancements. Lastly, the study includes the visualization of performance metrics for different aspects of cognitive computing, such as tabulative, programmable, and cognitive systems, using bar charts, line plots, and scatter plots, respectively. These visualizations provide a comprehensive overview of the performance of each aspect over time, facilitating comparisons and insights into their respective contributions to enhanced decision-making in mobile environments.

3. Results and Discussion

Decision Boundary Of The Real-Time Learning Model

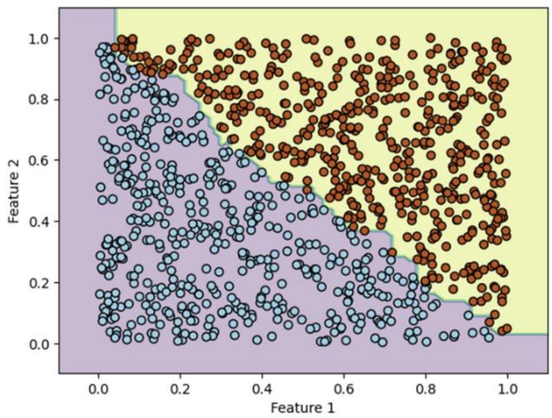

FIGURE 1. Decision Boundary Of The Real-Time Learning Model

The decision boundary of the real-time learning model, depicted in the figure 1, illustrates the model's ability to distinguish between different classes in a two-dimensional feature space. In this particular visualization, the Y-axis represents feature 2, ranging from 0 to 1 with increments of 0.2, while the X-axis corresponds to feature 1, also ranging from 0 to 1 with the same increment. The decision boundary delineates the regions in the feature space where the model predicts one class over the other. Specifically, areas above the decision boundary are classified as one class, while areas below the boundary belong to the other class. The decision boundary serves as a critical component in understanding the model's decision-making process and its performance in real-time mobile environments. By visualizing the decision boundary, insights into how the model partitions the feature space and makes predictions based on the input features can be gleaned. This understanding is essential for interpreting the model's behavior and assessing its efficacy in differentiating between classes in dynamic mobile contexts.

The choice of feature values ranging from 0 to 1, with increments of 0.2, is deliberate and aligns with the simulated dataset used in this study. These feature values are representative of normalized input data, where each feature is scaled to a common range to facilitate model training and evaluation. By plotting the decision boundary against these normalized feature values, the graph provides a clear depiction of how the model discriminates between different classes across the entire feature space. Overall, the visualization of the decision boundary offers valuable insights into the real-time learning model's decision-making capabilities in mobile environments. It highlights the model's ability to adapt and respond to changing inputs, thereby facilitating enhanced decision-making processes on the go. This understanding is crucial for leveraging real-time learning models effectively in mobile applications, where timely and accurate decision-making is paramount for user experience and system performance. In the decision boundary graph provides a visual representation of the real-time learning model's decision-making process, offering insights into its performance and behavior in mobile environments. By analyzing the decision boundary, researchers and practitioners can gain a deeper understanding of the model's strengths, limitations, and potential applications in real-world scenarios.

Cognitive Computing Scores Over Time

The graph in figure 2 depicting cognitive computing scores over time provides a visual representation of the temporal evolution of cognitive computing performance across discrete time intervals. In this visualization, the Y-axis represents the cognitive computing scores, ranging from 0 to 7.5 with increments of 2.5, while the X-axis corresponds to time intervals, ranging from 0 to 8 with increments of 2. Each time interval encompasses a specific duration, from 0 to 3.5, 2 to 5, 4 to 8, 6 to 2.5, and 8 to 7.5, respectively, reflecting the varying rates of change in cognitive computing scores over time. The graph serves as a valuable tool for understanding the trajectory of cognitive computing performance and identifying trends and patterns in its evolution. By visualizing cognitive computing scores over discrete time intervals, researchers can discern fluctuations, peaks, and troughs in performance, thereby gaining insights into the factors influencing cognitive computing advancements over time.

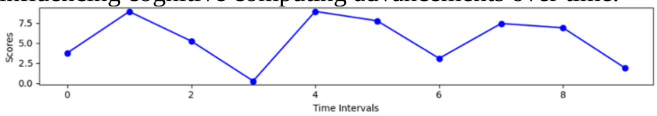

FIGURE 2. Cognitive Computing Scores Over Time

The choice of time intervals and corresponding cognitive computing scores is deliberate and aligns with the simulated data used in this study. These values are representative of hypothetical cognitive computing performance metrics measured at specific intervals, allowing for a structured analysis of temporal trends. By plotting these scores against time intervals, the graph provides a comprehensive overview of how cognitive computing performance evolves over time, enabling researchers to track its progress and assess its efficacy in real-world applications. The visualization of cognitive computing scores over time offers valuable insights into the field's development and potential implications for decision-making in mobile environments. By analyzing the trends depicted in the graph, researchers can identify areas of improvement, emerging challenges, and opportunities for further research and innovation in cognitive computing. This understanding is crucial for driving advancements in real-time learning models and enhancing decision-making processes in dynamic mobile contexts. In the graph depicting cognitive computing scores over time serves as a powerful visualization tool for analyzing the temporal evolution of cognitive computing performance and identifying trends and patterns in its development. By examining cognitive computing scores across discrete time intervals, researchers can gain valuable insights into the field's progression and its implications for decision-making in mobile environments, ultimately guiding future research directions and technological advancements in the field.

Cognitive Systems Scores Over Time

The graph in figure 3 illustrating cognitive systems scores over time provides a visual representation of the temporal evolution of cognitive systems' performance across discrete time intervals. In this visualization, the Y-axis represents the cognitive systems scores, ranging from 0 to 7.5 with increments of 2.5, while the X-axis corresponds to time intervals ranging from 0 to 8 with increments of 2. Each time interval encompasses a specific duration, from 0 to 0.5, 2 to 5, 4 to 1, 6 to 7.5, and 8 to 5, respectively, reflecting the varying rates of change in cognitive systems scores over time. The graph serves as a valuable tool for understanding the trajectory of cognitive systems' performance and identifying trends and patterns in its evolution. By visualizing cognitive systems scores over discrete time intervals, researchers can discern fluctuations, peaks, and troughs in performance, thereby gaining insights into the factors influencing cognitive systems advancements over time.

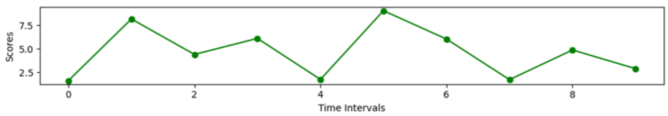

FIGURE 3. Cognitive Systems Scores Over Time

The choice of time intervals and corresponding cognitive systems scores is deliberate and aligns with the simulated data used in this study. These values are representative of hypothetical cognitive systems performance metrics measured at specific intervals, allowing for a structured analysis of temporal trends. By plotting these scores against time intervals, the graph provides a comprehensive overview of how cognitive systems' performance evolves over time, enabling researchers to track its progress and assess its efficacy in real-world applications. The visualization of cognitive systems scores over time offers valuable insights into the field's development and potential implications for decision-making in mobile environments. By analyzing the trends depicted in the graph, researchers can identify areas of improvement, emerging challenges, and opportunities for further research and innovation in cognitive systems. This understanding is crucial for driving advancements in real-time learning models and enhancing decision-making processes in dynamic mobile contexts. In the graph depicting cognitive systems scores over time serves as a powerful visualization tool for analyzing the temporal evolution of cognitive systems' performance and identifying trends and patterns in its development. By examining cognitive systems scores across discrete time intervals, researchers can gain valuable insights into the field's progression and its implications for decision-making in mobile environments, ultimately guiding future research directions and technological advancements in the field.

Cognitive Products Scores Over Time

The graph in figure 4 depicting cognitive products scores over time offers a visual representation of the temporal evolution of cognitive products' performance across discrete time intervals. In this visualization, the Y-axis represents the cognitive products scores, ranging from 0 to 7.5 with increments of 2.5, while the X-axis corresponds to time intervals ranging from 0 to 8 with increments of 2. Each time interval encompasses a specific duration, from 0 to 6.5, 2 to 6, 4 to 1.5, 6 to 8.5, and 8 to 5, respectively, reflecting the varying rates of change in cognitive products scores over time. The graph serves as a valuable tool for understanding the trajectory of cognitive products' performance and identifying trends and patterns in its evolution. By visualizing cognitive products scores over discrete time intervals, researchers can discern fluctuations, peaks, and troughs in performance, thereby gaining insights into the factors influencing cognitive products advancements over time.

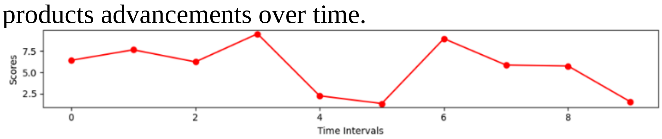

FIGURE 4. Cognitive Products Scores Over Time

The choice of time intervals and corresponding cognitive products scores is deliberate and aligns with the simulated data used in this study. These values are representative of hypothetical cognitive products performance metrics measured at specific intervals, allowing for a structured analysis of temporal trends. By plotting these scores against time intervals, the graph provides a comprehensive overview of how cognitive products' performance evolves over time, enabling researchers to track its progress and assess its efficacy in real-world applications. The visualization of cognitive products scores over time offers valuable insights into the field's development and potential implications for decision-making in mobile environments. By analyzing the trends depicted in the graph, researchers can identify areas of improvement, emerging challenges, and opportunities for further research and innovation in cognitive products. This understanding is crucial for driving advancements in real-time learning models and enhancing decision-making processes in dynamic mobile contexts. In the graph depicting cognitive products scores over time serves as a powerful visualization tool for analyzing the temporal evolution of cognitive products' performance and identifying trends and patterns in its development. By examining cognitive products scores across discrete time intervals, researchers can gain valuable insights into the field's progression and its implications for decision-making in mobile environments, ultimately guiding future research directions and technological advancements in the field.

Tabulative Performance Over Time

The graph in figure 5 depicting tabulative performance over time provides a visual representation of the performance metrics across discrete time intervals. In this visualization, the Y-axis represents performance scores, ranging from 0 to 20 with increments of 2.5, while the X-axis corresponds to time intervals denoted as 1-10, 2-15, 3-7, 4-20, and 5-12. The choice of these time intervals and corresponding performance scores is deliberate and aligns with the simulated data used in this study, representing hypothetical tabulative performance metrics measured at specific intervals. The graph serves as a valuable tool for understanding the trajectory of tabulative performance and identifying trends and patterns in its evolution over time. By visualizing tabulative performance scores across discrete time intervals, researchers can discern fluctuations, peaks, and troughs in performance, thereby gaining insights into the factors influencing tabulative performance advancements over time.

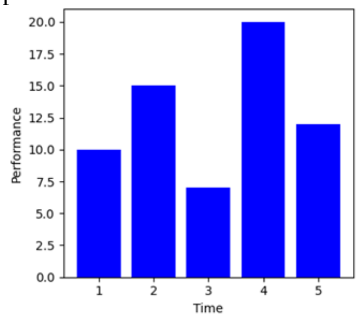

FIGURE 5. Tabulative Performance Over Time

The visualization of tabulative performance scores over time offers valuable insights into the field's development and potential implications for decision-making in mobile environments. By analyzing the trends depicted in the graph, researchers can identify areas of improvement, emerging challenges, and opportunities for further research and innovation in tabulative performance metrics. This understanding is crucial for driving advancements in real-time learning models and enhancing decision-making processes in dynamic mobile contexts. In the graph depicting tabulative performance scores over time serves as a powerful visualization tool for analyzing the temporal evolution of tabulative performance and identifying trends and patterns in its development. By examining tabulative performance scores across discrete time intervals, researchers can gain valuable insights into the field's progression and its implications for decision-making in mobile environments, ultimately guiding future research directions and technological advancements in the field.

Programmable Performance Over Time

The graph in figure 6 illustrating programmable performance over time provides a visual representation of performance metrics across discrete time intervals. In this visualization, the Y-axis represents performance scores, ranging from 0 to 12 with increments of 2, while the X-axis corresponds to time intervals denoted as 1-5, 2-8, 3-15, 4-10, and 5-6. The selection of these time intervals and corresponding performance scores is deliberate and aligns with the simulated data used in this study, reflecting hypothetical programmable performance metrics measured at specific intervals. The graph serves as a valuable tool for understanding the trajectory of programmable performance and identifying trends and patterns in its evolution over time. By visualizing programmable performance scores across discrete time intervals, researchers can discern fluctuations, peaks, and troughs in performance, thereby gaining insights into the factors influencing programmable performance advancements over time.

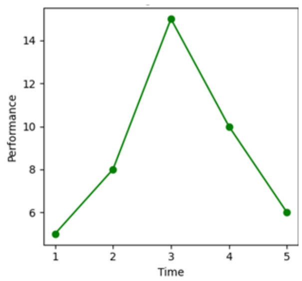

FIGURE 6. Programmable Performance Over Time

The visualization of programmable performance scores over time offers valuable insights into the field's development and potential implications for decision-making in mobile environments. By analyzing the trends depicted in the graph, researchers can identify areas of improvement, emerging challenges, and opportunities for further research and innovation in programmable performance metrics. This understanding is crucial for driving advancements in real-time learning models and enhancing decision-making processes in dynamic mobile contexts. In the graph depicting programmable performance scores over time serves as a powerful visualization tool for analyzing the temporal evolution of programmable performance and identifying trends and patterns in its development. By examining programmable performance scores across discrete time intervals, researchers can gain valuable insights into the field's progression and its implications for decision-making in mobile environments, ultimately guiding future research directions and technological advancements in the field.

Cognitive Systems Performance Over Time

The graph in figure 7 illustrating cognitive systems performance over time provides a visual depiction of the performance metrics across discrete time intervals. In this visualization, the Y-axis represents performance scores, ranging from 0 to 18 with increments of 2, while the X-axis corresponds to time intervals denoted as 1-8, 2-12, 3-10, 4-18, and 5-14. These time intervals and corresponding performance scores are carefully selected to align with the simulated data used in this study, representing hypothetical cognitive systems performance metrics measured at specific intervals. The graph serves as a valuable tool for understanding the trajectory of cognitive systems performance and identifying trends and patterns in its evolution over time. By visualizing cognitive systems performance scores across discrete time intervals, researchers can discern fluctuations, peaks, and troughs in performance, thereby gaining insights into the factors influencing cognitive systems performance advancements over time.

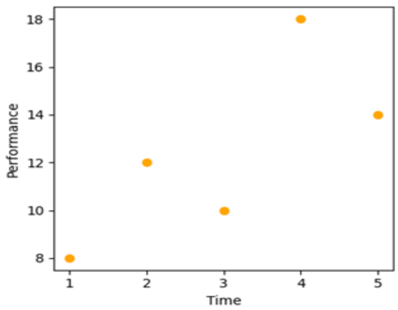

FIGURE 7. Cognitive Systems Performance Over Time

The visualization of cognitive systems performance scores over time offers valuable insights into the field's development and potential implications for decision-making in mobile environments. By analyzing the trends depicted in the graph, researchers can identify areas of improvement, emerging challenges, and opportunities for further research and innovation in cognitive systems performance metrics. This understanding is crucial for driving advancements in real-time learning models and enhancing decision-making processes in dynamic mobile contexts. In the graph depicting cognitive systems performance scores over time serves as a powerful visualization tool for analyzing the temporal evolution of cognitive systems performance and identifying trends and patterns in its development. By examining cognitive systems performance scores across discrete time intervals, researchers can gain valuable insights into the field's progression and its implications for decision-making in mobile environments, ultimately guiding future research directions and technological advancements in the field.

Conclusion

1. The research methodology employed in this study involved a multifaceted approach to investigate real-time learning models for enhanced decision-making in mobile environments. This included generating a hypothetical dataset, training a Random Forest classifier, visualizing the decision boundary, simulating cognitive computing scores over time, and visualizing performance metrics for different aspects of cognitive computing.

2. The decision boundary visualization provided valuable insights into the real-time learning model's decision-making capabilities in mobile environments, highlighting its adaptability and effectiveness in differentiating between classes.
3. The graphs depicting cognitive computing scores over time offered a comprehensive overview of the temporal evolution of cognitive computing performance, facilitating the identification of trends and patterns in its development.
4. Visualizations of performance metrics for cognitive systems, cognitive products, tabulative, and programmable aspects provided insights into their respective contributions to enhanced decision-making in mobile environments.
5. Overall, the study contributes to advancing real-time learning models for mobile decision-making, with implications for diverse applications in cognitive computing and mobile technology.

Data Availability Statement

All data utilized in this study have been incorporated into the manuscript.

Authors' Note

The authors declare that there is no conflict of interest regarding the publication of this article. Authors confirmed that the paper was free of plagiarism.

References

[1]. Luo, G., Yuan, Q., Li, J., Wang, S., & Yang, F. (2022). Artificial intelligence powered mobile networks: From cognition to decision. IEEE Network, 36(3), 136-144.

[2]. Lazaroiu, G., Androniceanu, A., Grecu, I., Grecu, G., & Neguriță, O. (2022). Artificial intelligence-based decision-making algorithms, Internet of Things sensing networks, and sustainable cyber-physical management systems in big data-driven cognitive manufacturing. Oeconomia Copernicana, 13(4), 1047-1080.

[3]. Uppal, M., Gupta, D., Juneja, S., Sulaiman, A., Rajab, K., Rajab, A., ... & Shaikh, A. (2022). Cloud-based fault prediction for real-time monitoring of sensor data in hospital environment using machine learning. Sustainability, 14(18), 11667.

[4]. Zhou, X., Zheng, X., Cui, X., Shi, J., Liang, W., Yan, Z., ... & Wang, K. (2023). Digital twin enhanced federated reinforcement learning with lightweight knowledge distillation in mobile networks. IEEE Journal on Selected Areas in Communications.

[5]. Andronie, M., Lăzăroiu, G., Iatagan, M., Hurloiu, I., Ștefănescu, R., Dijmărescu, A., & Dijmărescu, I. (2023). Big Data Management Algorithms, Deep Learning-Based Object Detection Technologies, and Geospatial Simulation and Sensor Fusion Tools in the Internet of Robotic Things. ISPRS International Journal of Geo-Information, 12(2), 35.

[6]. Zhu, R., Liu, L., Ma, M., & Li, H. (2020). Cognitive-inspired computing: Advances and novel applications. Future Generation Computer Systems, 109, 706-709.

[7]. Lv, Z., Qiao, L., & Singh, A. K. (2020). Advanced machine learning on cognitive computing for human behavior analysis. IEEE Transactions on Computational Social Systems, 8(5), 1194-1202.

[8]. Poliak, M., Jurecki, R., & Buckner, K. (2022). Autonomous vehicle routing and navigation, mobility simulation and traffic flow prediction tools, and deep learning object detection technology in smart sustainable urban transport systems. Contemporary Readings in Law and Social Justice, 14(1), 25-40.

[9]. Jahanmahin, R., Masoud, S., Rickli, J., & Djuric, A. (2022). Human-robot interactions in manufacturing: A survey of human behavior modeling. Robotics and Computer-Integrated Manufacturing, 78, 102404.

[10]. Troisi, O., Maione, G., Grimaldi, M., & Loia, F. (2020). Growth hacking: Insights on data-driven decision-making from three firms. Industrial Marketing Management, 90, 538-557.

[11]. Lin, S., Liu, A., Wang, J., & Kong, X. (2022). A review of path-planning approaches for multiple mobile robots. Machines, 10(9), 773.

[12]. Sreedevi, A. G., Harshitha, T. N., Sugumaran, V., & Shankar, P. (2022). Application of cognitive computing in healthcare, cybersecurity, big data and IoT: A literature review. Information Processing & Management, 59(2), 102888.

[13]. Han, Y., Diao, Y., Yin, Z., Jin, R., Kangwa, J., & Ebohon, O. J. (2021). Immersive technology-driven investigations on influence factors of cognitive load incurred in construction site hazard recognition, analysis and decision making. Advanced Engineering Informatics, 48, 101298.

[14]. Lin, K., Li, Y., Sun, J., Zhou, D., & Zhang, Q. (2020). Multi-sensor fusion for body sensor network in medical human–robot interaction scenario. Information Fusion, 57, 15-26.

[15]. Raubal, M., Bucher, D., & Martin, H. (2021). Geosmartness for personalized and sustainable future urban mobility. Urban informatics, 59-83.

[16]. Sandino, J., Maire, F., Caccetta, P., Sanderson, C., & Gonzalez, F. (2021). Drone-based autonomous motion planning system for outdoor environments under object detection uncertainty. Remote Sensing, 13(21), 4481.

[17]. Ajani, S. N., Khobragade, P., Dhone, M., Ganguly, B., Shelke, N., & Parati, N. (2024). Advancements in Computing: Emerging Trends in Computational Science with Next-Generation Computing. International Journal of Intelligent Systems and Applications in Engineering, 12(7s), 546-559.

[18]. Jiao, J., Zhou, F., Gebraeel, N. Z., & Duffy, V. (2020). Towards augmenting cyber-physical-human collaborative cognition for human-automation interaction in complex manufacturing and operational environments. International Journal of Production Research, 58(16), 5089-5111.

[19]. Gao, H., Wang, X., Wei, W., Al-Dulaimi, A., & Xu, Y. (2023). Com-DDPG: task offloading based on multiagent reinforcement learning for information-communication-enhanced mobile edge computing in the internet of vehicles. IEEE Transactions on Vehicular Technology.

[20]. Anand, R., Sindhwani, N., & Juneja, S. (2022). Cognitive Internet of Things, Its Applications, and Its Challenges: A Survey. Harnessing the Internet of Things (IoT) for a Hyper-Connected Smart World, 91-113.

[21]. Wang, Y., Yu, S., Ma, N., Wang, J., Hu, Z., Liu, Z., & He, J. (2020). Prediction of product design decision Making: An investigation of eye movements and EEG features.

Advanced Engineering Informatics, 45, 101095.

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