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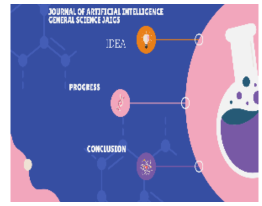

Crafting explainable artificial intelligence through active inference: A model for transparent introspection and decision-making

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ABSTRACT

This paper explores the feasibility of constructing interpretable artificial intelligence (AI) systems rooted in active inference and the free energy principle. Initially, we offer a concise introduction to active inference, emphasizing its relevance to modeling decision-making, introspection, and the generation of both overt and covert actions. Subsequently, we delve into how active inference can serve as a foundation for designing explainable AI systems. Specifically, it enables us to capture essential aspects of "introspective" processes and generate intelligible models of decision-making mechanisms. We propose an architectural framework for explainable AI systems employing active inference. Central to this framework is an explicit hierarchical generative model that enables the AI system to monitor and elucidate the factors influencing its decisions. Importantly, this model's structure is designed to be understandable and verifiable by human users. We elucidate how this architecture can amalgamate diverse data sources to make informed decisions in a transparent manner, mirroring aspects of human consciousness and introspection. Finally, we examine the implications of our findings for future AI research and discuss potential ethical considerations associated with developing AI systems with (apparent) introspective capabilities.

Introduction: Enhancing AI Explain ability with Active Inference

Artificial intelligence (AI) systems have permeated various sectors, from healthcare to finance, exhibiting remarkable performance. However, prevalent AI models, such as deep learning neural networks, often operate as "black boxes," lacking transparency in their decision-making processes. This opacity poses challenges, particularly in critical domains where understanding AI reasoning is crucial for trust and accountability.

The issue of explainable AI, commonly known as the "black box" problem, revolves around comprehending how AI models arrive at their decisions. Traditional machine learning approaches obscure the internal mechanisms that drive decision-making, hindering transparency and auditability. This lack of interpretability not only undermines trust but also impedes the identification and rectification of biases, perpetuating social inequalities.

Explainable AI endeavors to bridge this gap by providing human-understandable explanations for AI decisions and actions, fostering trust and collaboration between humans and AI systems. Regulatory bodies are increasingly emphasizing explainability as a prerequisite for trustworthy AI deployment, necessitating transparent AI architectures.

In this context, active inference, grounded in the free energy principle (FEP), emerges as a promising avenue for enhancing AI explainability. Active inference, a framework for modeling perception-action loops in cognitive systems, offers insights into introspective processes and hierarchical decision-making. By minimizing unexpected encounters with the environment, active inference enables adaptive behavior, facilitating self-awareness and self-reporting within AI systems.

This paper explores the integration of active inference principles into AI architectures to bolster explainability. We propose a novel AI framework based on explicit generative models, empowering AI systems to elucidate their decision-making processes in a comprehensible manner. By leveraging active inference, AI systems can not only enhance transparency but also facilitate meaningful collaboration between users and stakeholders.

In summary, this paper delves into the potential of active inference to advance AI explainability, addressing implications for future research and ethical considerations surrounding the development of introspective AI systems.

Active Inference and Introspection

Active inference provides a comprehensive framework for understanding, simulating, and elucidating the processes underlying decision-making, perception, and action. Rooted in the free energy principle (FEP), active inference has garnered significant attention in computational neuroscience and biology for its ability to model self-organizing systems effectively.

At its core, active inference models aim to minimize surprise, quantifying the deviation of a given trajectory from its characteristic path or expected sensory inputs. This principle underscores the optimization of a world model, representing the causal structure of observed outcomes. By minimizing surprise over time, the brain maintains a coherent internal model of the world, enhancing predictive accuracy and adaptability.

Active inference facilitates the modeling of fundamental aspects of human consciousness, particularly introspective self-access. Generative models serve as a crucial tool in active inference modeling, representing joint probability densities over latent causes and observable outcomes. These models offer interpretability and auditability, as the labeled factors explicitly delineate their contributions to the model's operations.

Figure 1 illustrates a simple generative model suitable for perceptual inference, while Figure 2 depicts a more intricate model tailored for action selection (policy selection). These models elucidate how observable outcomes are generated by underlying states or factors in the world.

Generative models, with their explicit labeling of factors, afford a level of interpretability and auditability absent in current black box approaches, making them invaluable for understanding and analyzing complex systems.

Active Inference, Introspection, and Self-Modeling

Active inference modeling has been instrumental in the scientific exploration of introspection, self-modeling, and self-access, contributing to the development of prominent theories of consciousness. Introspection, the capacity to assess one's own mental states and experiences, is pivotal for self-awareness, learning, and decision-making, constituting a cornerstone of human consciousness.

Self-modeling and self-access are intertwined processes crucial for fostering self-awareness and introspection. Self-modeling entails creating internal representations of oneself, while self-access involves accessing and engaging with these representations for self-improvement and learning. Together with introspection, these processes form a dynamic system that enhances our comprehension of consciousness and the self, potentially serving as the foundation for understanding ourselves and others.

Active inference has been employed to model introspective self-access through hierarchically structured generative models. The essence lies in enabling a system to report or evaluate its inferences by facilitating self-access, wherein certain components of the system utilize the output of others as input for further processing. This concept has been explored in computational neuroscience, characterized by the notions of "opacity" and "transparency." Transparent cognitive processes enable access to external phenomena without being perceptible themselves, akin to clear windows, while opaque processes do not afford such access.

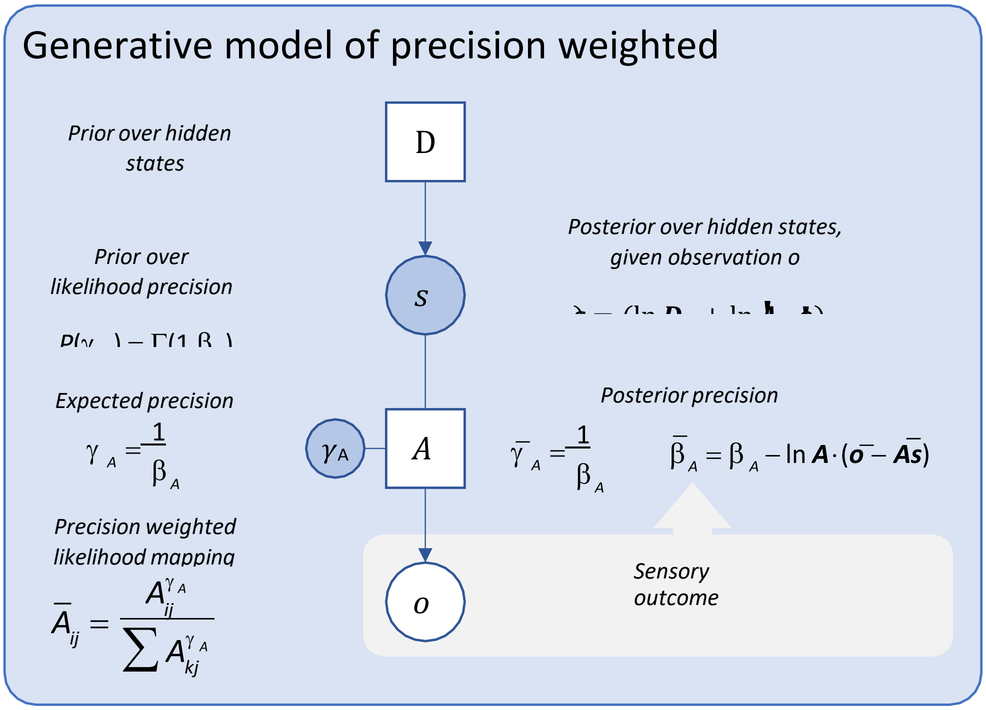

Figure 1: Basic Generative Model for Precision-Weighted Perceptual Inference

This figure illustrates a fundamental generative model designed for precision-weighted perceptual inference. The model consists of circles representing states, denoted in lowercase, where observable outcomes are labeled as "o" and latent states, subject to inference, are labeled as "s." Square symbols represent parameters, denoted in uppercase.

The likelihood mapping "A" connects outcomes to their underlying states, while "D" incorporates prior beliefs about states, independent of their sampling method. The precision term "γ" regulates the precision or weighting assigned to likelihood elements, implementing attention as precision-weighting.

This model serves as a foundation for understanding how perceptual inferences are weighted and processed, providing valuable insights into cognitive mechanisms. Figure adapted from [61].

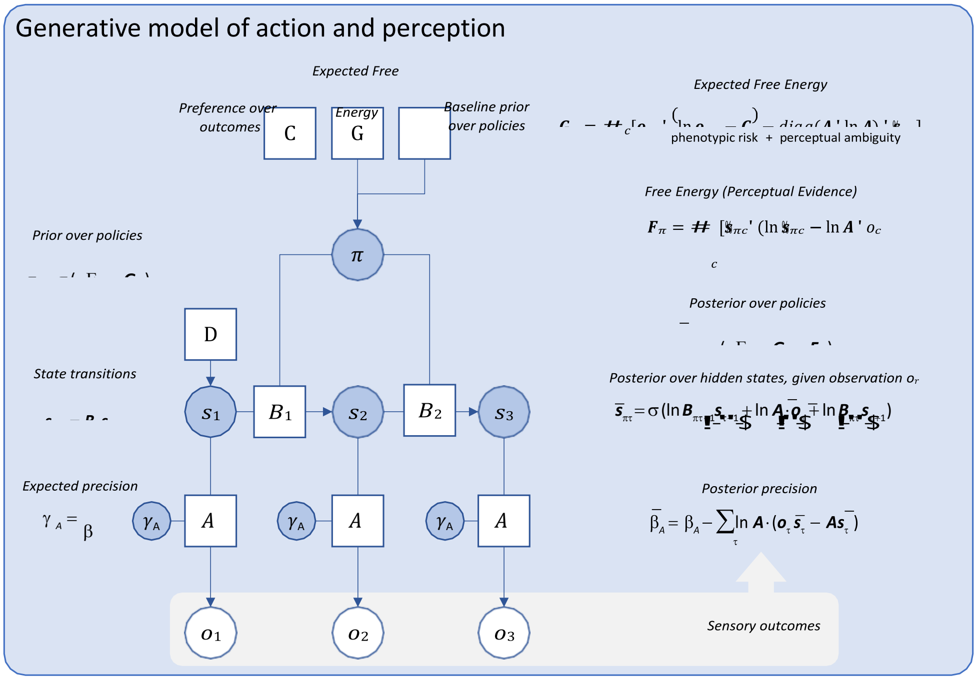

Figure 2: Generative Model for Policy Selection

This figure presents an advanced generative model tailored for planning and action selection. Building upon the basic model depicted in Figure 1, this model incorporates beliefs regarding the current course of action or policy, denoted as $\bar{\pi}$, along with additional parameters B, C, E, F, and G.

This expanded model generates a time series of states (s1, s2, etc.) and outcomes (o1, o2, etc.). The state transition parameter (B) governs the transition probabilities between states over time, independent of sampling methods. Parameters B, C, E, F, and G contribute to the selection of beliefs about courses of action, also known as policies.

The C vector specifies preferred or expected outcomes, influencing the calculation of variational (F) and expected (G) free energies. The E vector represents a prior preference for specific courses of action.

This model offers insights into the decision-making process, particularly in planning and selecting actions for the future. Figure adapted from [61].

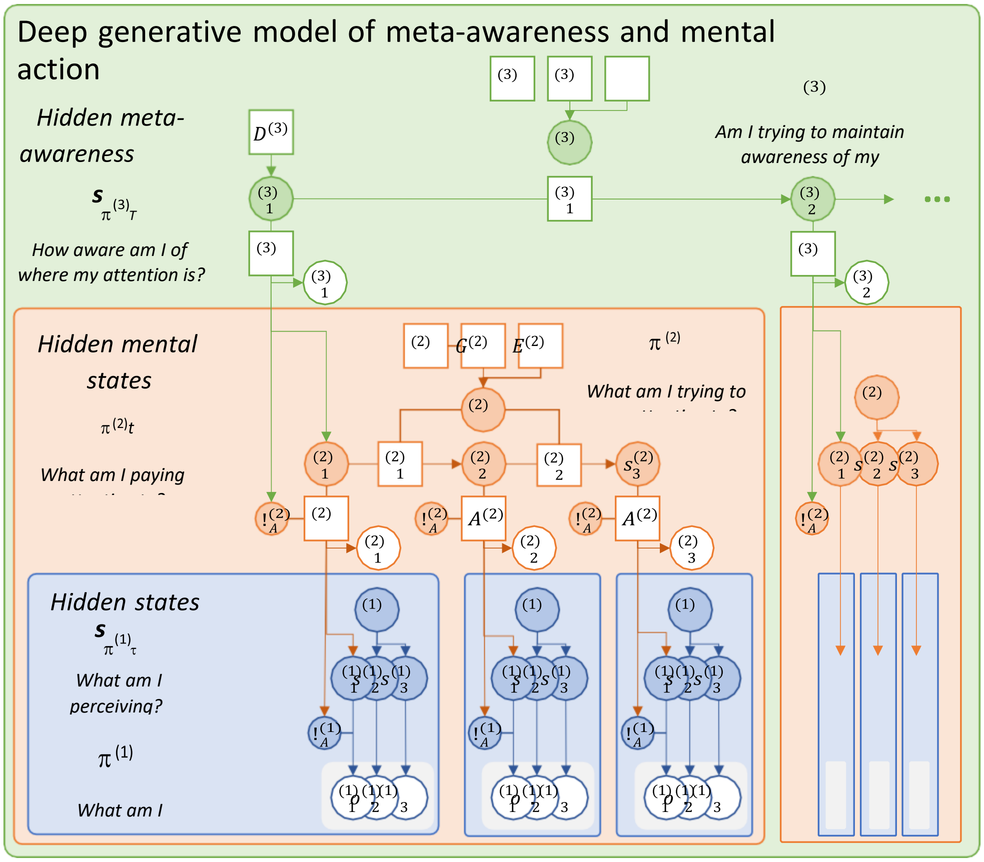

Figure 3: Hierarchical Generative Model with Self-Access

This figure illustrates a hierarchical generative model designed for self-access, building upon the architecture depicted in Figure 2. The basic generative model (depicted in blue) is augmented with two superordinate hierarchical layers.

In this architecture, posterior state estimates at one level are transmitted to the next level as data for further inference. This arrangement enables the system to make inferences about its own inferences, facilitating introspection and self-awareness.

Figure adapted from [61].

Utilizing Active Inference for Self-Explaining AI

Incorporating the principles of active inference into AI systems holds promise for enhancing explainability on two fronts. Firstly, by employing an explicit generative model, active inference-based AI systems are inherently designed to be interpretable and auditable by users familiar with such models. This potential for explainability can be further expanded by adopting standardized world modeling techniques, such as those under development by the IEEE P2874 Spatial Web Working Group, which formalize contextual relationships and enable real-time updates of digital twins of environments.

Secondly, by adopting an architecture inspired by active inference models of introspection, AI systems can access and report on the rationale behind their decisions and their mental state during decision-making. These systems can incorporate hierarchical self-access to enhance introspection, where both covert actions (internal computations and decision-making processes) and overt actions (external actions based on internal computations) can be recorded and explained. This deep inference fosters adaptability and responses to environmental changes.

The proposed AI architecture includes components that continuously update and maintain an internal model of its own states, beliefs, and goals, fostering introspection and enhanced explainability. By integrating metacognitive processing capabilities, the AI system can monitor, control, and evaluate its cognitive processes, leading to improved decision-making and explainability.

Furthermore, the AI architecture incorporates a self-report interface that translates the internal models and decision-making processes into human-understandable language. This interface facilitates communication between the AI system and human users, promoting trust and collaboration. Ultimately, this approach aims to emulate human-like consciousness and transparent introspection, leading to a deeper understanding of AI decision-making processes and improved collaboration between AI systems and human users.

Incorporating black box systems, such as large language models, into a generative model can aid AI systems in articulating their understanding of the world. Leveraging large language models for introspective interfaces can enhance explanations of belief updating and contribute to the overall performance and explainability of hybrid AI systems.

The proposed AI architecture utilizes attention mechanisms to enhance decision-making explainability by emphasizing important factors in the hierarchical generative model. Soft attention mechanisms dynamically compute attention weights based on input data and the AI system's internal state, allowing adaptive focus on relevant information.

In conclusion, integrating introspective processes into AI systems represents a significant step toward achieving more explainable AI. By leveraging explicit generative models, attention mechanisms, and introspection, AI systems can become more understandable, trustworthy, and adaptable. This integration bridges the gap between AI systems' internal computations and human users, paving the way for more sophisticated and ethically sound AI applications.

Discussion

Future Research Directions

The pursuit of explainable AI is crucial for understanding how AI models formulate their decisions, thereby averting biases and potential harm in their design and deployment. By integrating explicit generative models and introspective processing into AI architectures, we can develop systems capable of introspection, greatly enhancing their explainability and auditability. This approach not only addresses the problem of explainability but also fosters trust, fairness, and inclusivity in AI applications across various domains.

The development of AI architectures based on active inference opens up several avenues for future research. One direction involves further exploration of attention and introspection mechanisms in both AI systems and human cognition. Enhancing attentional models could improve the AI system's ability to focus on pertinent information during decision-making. Bridging AI with cognitive neuroscience by integrating biologically-inspired mechanisms offers insights into cognition and its application in AI, leading to more human-like systems capable of introspection and collaboration with humans.

Exploring advanced data fusion techniques, such as deep learning-based fusion or probabilistic fusion, holds promise for improving the AI system's ability to process multimodal data effectively. Evaluating these techniques across diverse domains will provide valuable insights. Moreover, enhancing the explanation dimension of AI systems is critical, particularly in decision-making scenarios, as it fosters trust and builds a rapport between AI and humans.

Additionally, computational phenomenology presents a promising direction for future research. Beckmann, Köstner, & Hipólito (2023) propose a framework that employs phenomenology to train machine learning models, offering a unique perspective on deep learning, consciousness, and their relation. Grounding AI training in sociocultural experience can mitigate biases and promote ethically sound AI systems. Incorporating computational phenomenology into AI architectures could enhance their introspective capabilities and understanding of human sociocultural contexts, fostering adaptability, trustworthiness, and meaningful collaboration with human users.

As we delve into these innovative approaches, we move closer to creating AI systems that mirror the richness and complexity of human cognition and consciousness, aligning with our goal of developing ethically responsible AI

Ethical Considerations of Introspective AI Systems

Ensuring ethical AI begins with the design of AI systems that prioritize transparency, auditability, explainability, and harm minimization. As these systems become more integrated into daily life, it is essential to address the ethical implications of introspective AI systems and develop regulatory frameworks for responsible AI use.

Introspective AI systems raise ethical concerns despite their potential for human-like decision-making and enhanced explainability. It remains critical to guarantee transparency, fairness, and unbiased decision-making while holding designers and users accountable for any resulting harm. Future research should focus on auditing AI decision-making processes, identifying and mitigating biases, and establishing ethical guidelines and regulatory frameworks for responsible deployment.

Moreover, as introspective AI systems become ubiquitous, issues related to agency, privacy, and data security may emerge. Safeguarding sensitive information and adhering to data protection regulations to protect agency will be paramount. Ultimately, ensuring responsible and transparent use of introspective AI systems is essential for their ethical deployment and broader societal acceptance.

Conclusion

In conclusion, active inference presents significant potential for advancing explainable AI by enhancing the auditability of decision-making processes, thereby increasing safety and user trust. By integrating active inference principles into AI design, we can create systems capable of human-like introspection and nuanced collaboration with users, bridging the gap between AI and cognitive neuroscience.

Our discussions underscore the importance of designing AI systems with active inference models as a foundation, enabling them to exhibit introspective capabilities and foster collaboration with humans. This approach not only promotes a deeper understanding of consciousness but also facilitates the development of more transparent, effective, and user-friendly AI applications tailored to diverse real-world scenarios.

As we progress in AI development, prioritizing explainable AI becomes increasingly crucial. By designing AI systems capable of making accurate decisions and providing understandable explanations, we promote trust and collaboration between AI systems and human users. This advancement leads to the creation of transparent, effective, and user-friendly AI applications adaptable to various real-world contexts.

References List:

[1]. Maharjan, R., Chy, M. S. H., Arju, M. A., & Cerny, T. (2023, June). Benchmarking Message Queues. In *Telecom* (Vol. 4, No. 2, pp. 298-312). MDPI. https://doi.org/10.3390/telecom4020018

[2]. Chy, M. S. H., Arju, M. A. R., Tella, S. M., & Cerny, T. (2023). Comparative Evaluation of Java Virtual Machine-Based Message Queue Services: A Study on Kafka, Artemis, Pulsar, and RocketMQ. *Electronics*, *12*(23), 4792. https://doi.org/10.3390/electronics12234792

[3]. Rahman, M., Chy, M. S. H., & Saha, S. (2023, August). A Systematic Review on Software Design Patterns in Today's Perspective. In *2023 IEEE 11th International Conference on Serious*

Games and Applications for Health (SeGAH) (pp. 1-8). IEEE. https://doi.org/10.1109/SeGAH57547.2023.10253758

[4]. Shivakumar, S. K., & Sethii, S. (2019). *Building Digital Experience Platforms: A Guide to Developing Next-Generation Enterprise Applications*. Apress.

[5]. Sethi, S., & Panda, S. (2024). Transforming Digital Experiences: The Evolution of Digital Experience Platforms (DXPs) from Monoliths to Microservices: A Practical Guide. *Journal of Computer and Communications*, *12*(2), 142-155. https://doi.org/10.4236/jcc.2024.122009

[6]. Sethi, P. Karmuru, & Tayal.(2023). Analyzing and Designing a Full-Text Enterprise Search Engine for Data-Intensive Applications. *International Journal of Science, Engineering and Technology*, *11*. https://www.ijset.in/wp-content/uploads/IJSET_V11_issue6_628.pdf

[7]. Sethi, S., Panda, S., & Kamuru, R. (2023). Comparative study of middle tier caching solution. *International Journal of Development Research*, *13*(11), 64225-64229.

[8]. Gitte, M., Bawaskar, H., Sethi, S., & Shinde, A. (2014). Content based video retrieval system. *International Journal of Research in Engineering and Technology*, *3*(06), 123-129.

[9]. Gitte, M., Bawaskar, H., Sethi, S., & Shinde, A. (2014). Content based video retrieval system. *International Journal of Research in Engineering and Technology*, *3*(06), 123-129.

[10]. Sethi, S., & Shivakumar, S. K. (2023). DXPs Digital Experience Platforms Transforming Fintech Applications: Revolutionizing Customer Engagement and Financial Services. *International Journal of Advance Research, Ideas and Innovations in Technology*, *9*, 419-423.

[11]. Sethi, S., Panda, S., & Hooda, S. (2024). Design and Optimization of a Zookeeper and Kafka-Based Messaging Broker for Asynchronous Processing in High Availability and Low Latency Applications. *J Curr Trends Comp Sci Res*, *3*(2), 01-07.

[12]. Li, Z., Zhu, H., Liu, H., Song, J., & Cheng, Q. (2024). Comprehensive evaluation of Mal-API-2019 dataset by machine learning in malware detection. *arXiv preprint arXiv:2403.02232*.

https://doi.org/10.48550/arXiv.2403.02232

[13]. Jhurani, J. REVOLUTIONIZING ENTERPRISE RESOURCE PLANNING: THE IMPACT OF ARTIFICIAL INTELLIGENCE ON EFFICIENCY AND DECISION-MAKING FOR CORPORATE STRATEGIES.

[13]. Jhurani, J. Enhancing Customer Relationship Management in ERP Systems through AI: Personalized Interactions, Predictive Modeling, and Service Automation.

[14]. Jhurani, J. DRIVING ECONOMIC EFFICIENCY AND INNOVATION: THE IMPACT OF WORKDAY FINANCIALS IN CLOUD-BASED ERP ADOPTION.

[15]. Smith, J. D. (2024). The Impact of Technology on Sales Performance in B2B Companies. *Journal of Artificial Intelligence General science (JAIGS) ISSN: 3006-4023*, *3*(1), 86-102.

https://doi.org/10.60087/jaigs.vol03.issue01.p102

[16]. Deep Smith, J. (2024). 2019 to 2024, The State of Sales Management Research in the Latin America. *International Journal of Engineering, Management and Humanities (IJEMH)*, *5*(1), 223-226.

[17]. Smith, J. D. Influence of Self-Efficacy, Stress, and Culture on the Productivity of Industrial Sales Executives in Latin American Sales Networks.

[18]. Miah, S., Rahaman, M. H., Saha, S., Khan, M. A. T., Islam, M. A., Islam, M. N., ... & Ahsan, M. H. (2013). Study of the internal structure of electronic components RAM DDR-2 and motherboard of nokia-3120 by using neutron radiography technique. *International Journal of Modern Engineering Research (IJMER), 3*(60), 3429-3432

[19]. Rahaman, M. H., Faruque, S. B., Khan, M. A. T., Miah, S., & Islam, M. A. (2013). Comparison of General Relativity and Brans-Dicke Theory using Gravitomagnetic clock effect. *International Journal of Modern Engineering Research*, *3*, 3517-3520.

[20]. Miah, M. H., & Miah, S. (2015). The Investigation of the Effects of Blackberry Dye as a Sensitizer in TiO2 Nano Particle Based Dye Sensitized Solar Cell. *Asian Journal of Applied Sciences*, *3*(4).

[21]. Miah, S., Miah, M. H., Hossain, M. S., & Ahsan, M. H. (2018). Study of the Homogeneity of Glass Fiber Reinforced Polymer Composite by using Neutron Radiography. *Am. J. Constr. Build. Mater*, *2*, 22-28.

[22]. Miah, S., Islam, G. J., Das, S. K., Islam, S., Islam, M., & Islam, K. K. (2019). Internet of Things (IoT) based automatic electrical energy meter billing system. *IOSR Journal of Electronics and Communication Engineering*, *14*(4 (I)), 39-50.

[23]. Nadia, A., Hossain, M. S., Hasan, M. M., Islam, K. Z., & Miah, S. (2021). Quantifying TRM by modified DCQ load flow method. *European Journal of Electrical Engineering*, *23*(2), 157-163.

[24]. Miah, S., Raihan, S. R., Sagor, M. M. H., Hasan, M. M., Talukdar, D., Sajib, S., ... & Suaiba, U. (2022). Rooftop Garden and Lighting Automation by the Internet of Things (IoT). *European Journal of Engineering and Technology Research*, *7*(1), 37-43.

DOI: https://doi.org/10.24018/ejeng.2022.7.1.2700

[25]. Prasad, A. B., Singh, S., Miah, S., Singh, A., & Gonzales-Yanac, T. A Comparative Study on Effects of Work Culture on employee satisfaction in Public & Private Sector Bank with special reference to SBI and ICICI Bank.

[26]. Ravichandra, T. (2022). A Study On Women Empowerment Of Self-Help Group With Reference To Indian Context.

https://www.webology.org/data-cms/articles/20220203075142pmwebology%2019%20(1)%20-%2053.pdf

[27]. Kumar, H., Aoudni, Y., Ortiz, G. G. R., Jindal, L., Miah, S., & Tripathi, R. (2022). Light weighted CNN model to detect DDoS attack over distributed scenario. *Security and Communication Networks*, *2022*.

https://doi.org/10.1155/2022/7585457

[28]. Ma, R., Kareem, S. W., Kalra, A., Doewes, R. I., Kumar, P., & Miah, S. (2022). Optimization of electric automation control model based on artificial intelligence algorithm. *Wireless Communications and Mobile Computing*, *2022*.

https://doi.org/10.1155/2022/7762493

[29]. Devi, O. R., Webber, J., Mehbodniya, A., Chaitanya, M., Jawarkar, P. S., Soni, M., & Miah, S. (2022). The Future Development Direction of Cloud-Associated Edge-Computing Security in the Era of 5G as Edge Intelligence. *Scientific Programming*, *2022*.

https://doi.org/10.1155/2022/1473901

[30]. Al Noman, M. A., Zhai, L., Almukhtar, F. H., Rahaman, M. F., Omarov, B., Ray, S., ... & Wang, C. (2023). A computer vision-based lane detection technique using gradient threshold and hue-lightness-saturation value for an autonomous vehicle. *International Journal of Electrical and Computer Engineering*, *13*(1), 347.

[31]. Patidar, M., Shrivastava, A., Miah, S., Kumar, Y., & Sivaraman, A. K. (2022). An energy efficient high-speed quantum-dot based full adder design and parity gate for nano application. *Materials Today: Proceedings*, *62*, 4880-4890.https://doi.org/10.1016/j.matpr.2022.03.532

[32]. Pillai, A. S. (2023). Advancements in Natural Language Processing for Automotive Virtual Assistants Enhancing User Experience and Safety. *Journal of Computational Intelligence and Robotics*, *3*(1), 27-36.

[33]. Rehan, H. (2024). Revolutionizing America's Cloud Computing the Pivotal Role of AI in Driving Innovation and Security. *Journal of Artificial Intelligence General science (JAIGS) ISSN: 3006-4023*, *2*(1), 189-208. DOI: https://doi.org/10.60087/jaigs.v2i1.p208

[34]. Rehan, H. (2024). AI-Driven Cloud Security: The Future of Safeguarding Sensitive Data in the Digital Age. *Journal of Artificial Intelligence General science (JAIGS) ISSN: 3006-4023*, *1*(1), 47-66.
DOI: https://doi.org/10.60087/jaigs.v1i1.p66

[35]. Rahman, S., Mursal, S. N. F., Latif, M. A., Mushtaq, Z., Irfan, M., & Waqar, A. (2023, November). Enhancing Network Intrusion Detection Using Effective Stacking of Ensemble Classifiers With Multi-Pronged Feature Selection Technique. In *2023 2nd International*

Conference on Emerging Trends in Electrical, Control, and Telecommunication Engineering (ETECTE) (pp. 1-6). IEEE. https://doi.org/10.1109/ETECTE59617.2023.10396717

[36]. Latif, M. A., Afshan, N., Mushtaq, Z., Khan, N. A., Irfan, M., Nowakowski, G., ... & Telenyk, S. (2023). Enhanced classification of coffee leaf biotic stress by synergizing feature concatenation and dimensionality reduction. *IEEE Access*. https://doi.org/10.1109/ACCESS.2023.3314590

[37]. Irfan, M., Mushtaq, Z., Khan, N. A., Mursal, S. N. F., Rahman, S., Magzoub, M. A., ... & Abbas, G. (2023). A Scalo gram-based CNN ensemble method with density-aware smote oversampling for improving bearing fault diagnosis. *IEEE Access*, *11*, 127783-127799.

https://doi.org/10.1109/ACCESS.2023.3332243

[38]. Irfan, M., Mushtaq, Z., Khan, N. A., Althobiani, F., Mursal, S. N. F., Rahman, S., ... & Khan, I. (2023). Improving Bearing Fault Identification by Using Novel Hybrid Involution-Convolution Feature Extraction with Adversarial Noise Injection in Conditional GANs. *IEEE Access*. https://doi.org/10.1109/ACCESS.2023.3326367

[39]. Latif, M. A., Mushtaq, Z., Arif, S., Rehman, S., Qureshi, M. F., Samee, N. A., ... & Al-masni, M. A. Improving Thyroid Disorder Diagnosis via Ensemble Stacking and Bidirectional Feature Selection. https://www.techscience.com/cmc/v78n3/55928/html

[40]. Jimmy, F. N. U. (2024). Cyber security Vulnerabilities and Remediation Through Cloud Security Tools. *Journal of Artificial Intelligence General science (JAIGS) ISSN: 3006-4023*, *3*(1), 196-233. https://doi.org/10.60087/jaigs.vol03.issue01.p233

[41]. Gunasekaran, K. P., Babrich, B. C., Shirodkar, S., & Hwang, H. (2023, August). Text2Time: Transformer-based Article Time Period Prediction. In *2023 IEEE 6th International Conference on Pattern Recognition and Artificial Intelligence (PRAI)* (pp. 449-455). IEEE. https://doi.org/10.1109/PRAI59366.2023.10331985

[42]. Gunasekaran, K., & Jaiman, N. (2023, August). Now you see me: Robust approach to partial occlusions. In *2023 IEEE 4th International Conference on Pattern Recognition and Machine Learning (PRML)* (pp. 168-175). IEEE. https://doi.org/10.1109/PRML59573.2023.10348337

[43]. Kommaraju, V., Gunasekaran, K., Li, K., Bansal, T., McCallum, A., Williams, I., & Istrate, A. M. (2020). Unsupervised pre-training for biomedical question answering. *arXiv preprint arXiv:2009.12952*. https://doi.org/10.48550/arXiv.2009.12952

[44]. Bansal, T., Gunasekaran, K., Wang, T., Munkhdalai, T., & McCallum, A. (2021). Diverse distributions of self-supervised tasks for meta-learning in NLP. *arXiv preprint arXiv:2111.01322*. https://doi.org/10.48550/arXiv.2111.01322

[45]. Padmapriya, V. M., Thenmozhi, K., Hemalatha, M., Thanikaiselvan, V., Lakshmi, C., Chidambaram, N., & Rengarajan, A. (2024). Secured IIoT against trust deficit-A flexi cryptic approach. *Multimedia Tools and Applications*, 1-28. https://doi.org/10.1007/s11042-024-18962-x

[46]. Bansal, T., Gunasekaran, K., Wang, T., Munkhdalai, T., & McCallum, A. (2021). Diverse distributions of self-supervised tasks for meta-learning in NLP. *arXiv preprint arXiv:2111.01322*.

https://doi.org/10.48550/arXiv.2111.01322

[47]. Gunasekaran, K., Tiwari, K., & Acharya, R. (2023, June). Utilizing deep learning for automated tuning of database management systems. In *2023 International Conference on Communications, Computing and Artificial Intelligence (CCCAI)* (pp. 75-81). IEEE.

https://doi.org/10.1109/CCCAI59026.2023.00022

[48]. Gunasekaran, K. P. (2023, May). Ultra sharp: Study of single image super resolution using residual dense network. In *2023 IEEE 3rd International Conference on Computer Communication and Artificial Intelligence (CCAI)* (pp. 261-266). IEEE.

https://doi.org/10.1109/CCAI57533.2023.10201303

[49]. Kumar, S. (2023). Digital Twin-A Key Driver to Transform North American Railroad. *International Journal of Computer Applications (IJCA)*, *4*(1).