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Editorial: Augmented Intelligence for Enabling Knowledge-Driven Decision Making

Heru Agus Santoso[1*]

[1] Faculty of Computer Science, Universitas Dian Nuswantoro, Imam Bonjol Street No. 207 (H Building) Semarang, Indonesia

**corresponding author: (heru.agus.santoso@dsn.dinus.ac.id; ORCiD: 0000-0002-5436-1739)*

Abstract - More flexible and cooperative decision-making processes are required as a result of society's digital transformation. The role of augmented intelligence, that is the synergistic fusion of artificial intelligence and human judgment in facilitating knowledge-driven strategies across various domains is examined in this thematic issue. The integration of business intelligence and software engineering, which forms the foundation for creating intelligent, scalable, and explicable systems, is essential to this investigation. The six chosen papers in this issue show how machine learning techniques can be used to mine and model both structured (such as health records indicators) and unstructured (such as product reviews, e-sports discourse, and social media text from X) data. Applications in political sentiment analysis, geopolitical opinion monitoring, risk communication related to weather, e-commerce consumer feedback, gaming community analytics, and mapping malnutrition for public health intervention are all covered in these papers. From explainability and interface design to data preprocessing and model deployment, software engineering is essential to coordinating these intelligent pipelines and guaranteeing that AI outputs are not only accurate but also practically sound. The pieces in this issue collectively demonstrate how Augmented Intelligence can transform decision-making in a rapidly changing digital society when enabled by domain-aware data pipelines and structured engineering frameworks.

Keywords— Augmented Intelligence, Digital Society, Knowledge-driven Decision Making, Machine Learning, Deep Learning

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1. INTRODUCTION

Modern society's rapid digitisation has changed how people, businesses, and governments use data, make decisions, and create policies. Augmented Intelligence, a paradigm that stresses the cooperative fusion of computational intelligence and human expertise, is at the vanguard of this shift [1]. Unlike AI systems meant to function by themselves augmented intelligence (AI) systems have the objective of improving human thinking, creativity, and judgement instead of replacing them. The changing digital society, in which conclusions must be informed, ethically acceptable, and context-aware, relies upon this concept. Augmented intelligence utilises either structured (such as demographic characteristics and anthropometric records) as well as unstructured (such as social media and user reviews) data using sophisticated algorithms for machine learning while involving humans for context-dependent decision-making, interpretation, and regulation [2]. This method is more appropriate with actual global problems

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where transparency, adaptability, and cooperation are essential. By contrast, typical artificial intelligence systems frequently give human intervention and explainability second priority across automation and the optimization process. The change from artificial intelligence to augmented intelligence suggests an important reorientation from "replacing people" to "empowering people via intelligent systems". Recent shifts in the industry have started filling these gaps. Emerging frameworks integrating explainable artificial intelligence (XAI) technologies including SHAP and LIME with deep learning algorithms like Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), and Multi-Head Attention [3], [4] offer more interpretable results along with consistent decisions. Unsupervised machine learning techniques like clustering, for instance, K-Means, Latent Dirichlet Allocation (LDA), Density-Based Spatial Clustering of Applications with Noise (DBSCAN) have been further improved to uncover hidden patterns in large consumer, social, and health data. In addition, reliable software pipelines made up of data gathering, preprocessing, modeling purposes, and validation have transformed into full-stack augmented intelligence systems applicable in real-world applications.

1.1 Recent Development in Augmented Intelligence

Present innovations in augmented intelligence sound to be most impacted by the combined use of machine learning, explainable artificial intelligence, and human-focused design of systems [5]. These developments constitute a component of a growing trend against AI systems that primarily concentrate on automation and also toward frameworks which enable strategic decision-making in complex, data-rich settings while boosting human cognitive abilities. Among those that are most obvious modifications are those which combine attention mechanisms like Multi-Head Attention (MHA) with deep learning architectures [6]. Thus, it enables models to continually utilise significant features in unstructured streams as well as data structures [7]. Along with domain-specific engineering of features, all of these models such as the hybrid combinations of deep learning models are demonstrating more predictive power in fields such risk analysis, sentiment analysis, and public health assessments [8].

At the same time, the need of XAI frameworks such as LIME (Local Interpretable Model-agnostic Explanations) or SHAP (SHapley Additive exPlanations) has risen [9], [10]. These tools provide model prediction openness and responsibility, therefore assisting domain experts not only data scientists with assessing outcomes, proving recommendations, and preserving control over significant decisions. Augmented intelligence in this scenario encourages cooperative interpretation instead of highlighting uncertain automation. Developments in software engineering as well—such as adaptable Application Programming Interfaces (API)-driven frameworks, low-latency deployment settings, and MLOps pipelines incorporating Development and Operations (DevOps) in the life cycle of machine learning that generate consistent and measurable Machine Learning (ML) systems have additionally contributed to the practical implementation possibility [11], [12]. These systems enable continuous monitoring and learning, therefore allowing AI-enhanced platforms to change with user input and evolving environment [13]. The field of augmented intelligence has also seen more application. It enables real-time monitoring of policy sentiment in public sector governance [14]. In the medical sector, it promotes focused intervention and early detection [15]. In digital gaming and commerce, it enables adaptive engagement strategies and user insight modelling. Importantly, these apps need increasingly varied data sources, including unstructured social media streams and structured databases, which requires both semantic integration and technical interoperability. These advances taken together indicate that augmented intelligence is now a deployable, multi-layered system architecture capable of addressing the practical issues of the digital age rather than only a theoretical framework [16].

1.2 Opportunities for Future Research in Augmented Intelligence

Augmented intelligence is still a fairly new research paradigm with much untapped potential even with its growing appeal. Machine learning combined with human insight continues to generate fresh research possibilities in technical, application-driven, and methodological domains. One interesting possibility is the development of adaptive systems with user-in-the-loop that enable real-time human-AI agent cooperation [17]. Though they cannot enable interactive decision refinement, which lets human users ask questions, make corrections, or co-create outcomes with the system, current models often focus on prediction efficiency or accuracy. Future studies have to look at dynamic feedback loops, tailored model adjustment, and trust calibration mechanisms if they are to help systems fit users' mental models and contextual knowledge [18]. Moreover, a vital field of study is the design of multi-modal augmented intelligence systems [19]. The majority of current implementations only use unstructured text data or structured tabular data. But real-world issues, especially in areas like governance, public health, and climate change, call for systems that can integrate and reason across a variety of data types, such as time-series sensor data, images, geospatial data, and natural language. Constructing computationally efficient and semantically coherent fusion architectures is a challenge [18]. Formalising explainability and ethical alignment in augmented intelligence workflows presents another important opportunity. In order to enable interpretable-by-design models, explainability must be incorporated at the architectural level, even though XAI techniques like SHAP and LIME provide post hoc interpretations [20]. Furthermore, a route towards responsible augmented intelligence that is consistent with social norms and human values is represented by the integration of ontologies, domain-specific knowledge bases, and fairness-aware optimisation [21].

More scientific research needs to be done on the role of software engineering in operationalizing augmented intelligence. How best to facilitate ongoing model integration (via MLOps), high-stakes validation, and maintenance of systems that need to co-evolve with human behavior and knowledge is still debated [22]. It is important to investigate engineering patterns for human-centered AI applications, such as modular APIs, auditability features, and hybrid-cloud infrastructure [23]. Finally, there is a strong case for investigating augmented intelligence in group decision-making. Individual decision support is the primary focus of most implementations, but collaborative intelligence systems that support multi-stakeholder negotiation, pluralistic reasoning, and consensus building are needed for many of today's societal problems, from public health policy to climate response. There is still much to be learned about designing platforms that facilitate this level of coordination. These opportunities demonstrate that augmented intelligence is a rich interdisciplinary field at the intersection of artificial intelligence, cognitive science, software engineering, and ethical systems design rather than a solved problem. By investigating these aspects more thoroughly, researchers can ensure that intelligent systems remain not only highly technologically advanced but also socially responsive, open and genuinely cooperative in developing digital society.

2. IN THIS THEMATIC ISSUE

Organised into three thematic areas, six original research articles in this thematic issue demonstrate how multiple forms of Augmented Intelligence assists knowledge-driven decision-making in political, social, health, and business settings. Each study leverages structured or unstructured data, ranging from anthropometric health records to real-time social media streams and applies robust machine learning or data mining techniques.

2.1 Augmented Intelligence for Public Sentiment and Societal Monitoring

a. Angga et al.'s work entitled "Sentiment Analysis of the 2024 General Election Through Twitter using Long-Short-Term Memory Algorithm" concerning the 2024 Indonesian General Election employs an LSTM-based deep learning method employed on tweets obtained over six weeks. Demonstrating reliable results in political conversation analysis, the model reached 84% accuracy throughout three sentiment categories: positive, neutral, and negative. While an equal number of samples was generated by random oversampling, data preprocessing comprised tokenization, stemming, and lexicon-based labeling. Real-time public opinion tracking has been made feasible by a Streamlit-based interface generated to allow people without technical expertise to use the sentiment approach. The research shows how augmented intelligence allows election participants to make informed, timely decisions by utilizing structured Natural Language Processing (NLP) workflows as well as interactive software methods.

b. Noori et al.'s work " Sentiment Analysis of the Israel-Palestine Conflict on Twitter: Insights from the Indonesian Perspective using a Long Short-Term Memory Algorithm" examining 1,700 tweets using the LSTM algorithm, this work analyses Indonesian public opinion on the conflict between Israel and Palestine. Providing knowledge about the development of public attitudes, the analysts classified tweets as positive, neutral, or negative, employing text preprocessing approaches and lexicon-based sentiment labeling. The LSTM model have been chosen for its inherent ability to identify temporal as well as contextual relationships within sequential language data. Visualised via sentiment distribution and confusion matrix evaluation, the conclusions reveal the majority of negative sentiment and the temporal variation of public reactions. By integrating machine learning alongside real-time social data, this work demonstrates why augmented intelligence could potentially utilised for geopolitical analysis to advise public discourse and policy evaluation.

c. Abdurahmonov et al.'s work " Aspects-Based Sentiment Analysis of Indonesia's Extreme Weather On Twitter Using Long Short - Term" provides an LSTM-based aspect-based sentiment analysis method described for assessing Indonesian public opinions regarding extreme weather events on Twitter. Using a lexicon-based strategy, tweets are categorised into positive, neutral, as well as negative sentiments according to three key factors: weather form, prediction, and government/community reaction. Showing consistent results on unstructured social media data, the LSTM model obtains high accuracy rates of 98.94% for aspect categorization and 97.53% for sentiment classification. This study increases the ability to be understood of climate-related sentiment analysis through combining deep learning with a structured classification system. By integrating machine learning knowledge with practical communication strategy for responding to emergencies planners and legislators, this article demonstrates Augmented Intelligence application.

2.2 Intelligent Systems for Digital Commerce and Gaming Ecosystems

a. Anam et al.'s work "Classification of Smartphone Product Reviews on E-Commerce using the Recurrent Neural Network (RNN) Method" applies RNN to classify smartphone user reviews on e-commerce platforms into positive and negative sentiment categories. A dataset of 752 reviews was collected, preprocessed, and balanced using random oversampling to improve model performance. The RNN model achieved 95.13% accuracy, demonstrating its robustness in handling real-world user-generated text data. The authors emphasise the role of augmented intelligence, highlighting how AI-generated sentiment insights can empower decision makers to refine product features and marketing strategies. The paper illustrates the integration of machine learning and human insights in digital commerce, where a structured workflow translates consumer feedback into actionable business intelligence.

b. Muhammad et al.'s work "Sentiment Analysis and Topic Modeling on X Related to Mobile Legends: Bang Bang Game Using Lexicon-Based, LDA, and SVM" analyses 4,313 tweets related to the Mobile Legends: Bang Bang (MLBB) gaming community, applying a combination of lexicon-based sentiment analysis, Latent Dirichlet Allocation (LDA) for topic modeling, and Support Vector Machine (SVM) for classification. The sentiment distribution reveals that 70.8% of tweets are neutral, 22.4% are positive, and 6.9% are negative, with sentiment topics ranging from gameplay and teams to in-game content and rewards. The SVM model achieves 90.57% accuracy, demonstrating strong performance in handling high-dimensional text data. Topic modeling further uncovers latent thematic structures, helping developers and strategists understand community discourse. This paper exemplifies augmented intelligence in digital entertainment by transforming unstructured social media data into actionable insights for engagement optimization and community-responsive development.

2.3 Intelligent Systems for Digital Commerce and Gaming Ecosystems

"K-Means Clustering Optimisation of Toddler Malnutrition Status Using Elbow Method" by Widyawati et al. determines the distribution of malnutrition prevalence across sub-districts in an Indonesian city using a dataset of 9,594 toddler records and a K-Means clustering algorithm. The authors identified two ideal clusters representing sub-districts with low and high malnutrition prevalence using the Elbow Method, Davies-Bouldin Index (DBI = 0.361), and Silhouette Score (0.799). The system provides local governments an in-depth understanding of nutritional differences and lets them carry out spatially concentrated health interventions. By including these findings through the Knowledge Discovery in Database (KDD) framework, the study demonstrates Augmented Intelligence via AI-assisted interpretable patterns identification with important practical use. It demonstrates how unsupervised learning could guide public health policies while ensuring human oversight understanding sensitive health data.

These studies demonstrated the interdisciplinary potential of augmented intelligence when combined with robust software pipelines as well as domain-driven application design. Supported by efficient engineering and interpretability tools, they illustrate how algorithms based on machine learning could turn data into practical, actionable information across a variety of digital environments.

3. CONCLUSION

The transformative potential of augmented intelligence in facilitating strategic, knowledge-driven decision-making across various digital society sectors is highlighted in this thematic issue. These systems facilitate more open, flexible, and moral decision-making processes by fusing cutting-edge machine learning methods with human discretion and contextual awareness. From nutritional status mapping to electoral sentiment monitoring, the six chosen papers demonstrate how both structured and unstructured data can be used through carefully designed pipelines to solve practical issues. Importantly, the incorporation of software engineering principles guarantees that these intelligent models are not only accurate but also scalable, operationally sustainable, and explicable. Explainability, human-in-the-loop design, and ethical alignment will play an increasingly important role in the impact of augmented intelligence systems as they develop. This compilation adds to the increasing amount of evidence showing that intelligent systems need to be developed to enhance human intelligence and capability rather than just automate tasks. In order to create human-centered, responsive AI systems for changing digital societies, we hope that the ideas and approaches presented in this issue will stimulate more interdisciplinary research and innovation.

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No conflict of interests were disclosed.

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BIOGRAPHIES OF AUTHORS

	**Heru Agus Santoso** is a faculty member at Faculty of Computer Science, Universitas Dian Nuswantoro, Indonesia. and researcher at the Center for Medical Technology Innovation (CEMTI). His research interests include machine learning, biomedical data analysis, and software engineering for health systems. He published in various international journals on topics such as explainable deep learning, and decision support systems. As a guest editor, he is committed to promoting interdisciplinary approaches that integrate AI with real-world applications in healthcare and strategic decision-making. His email is heru.agus.santoso@dsn.dinus.ac.id.