

Deep Learning Approaches for Natural Language Processing

Aleksandra Świetlicka ^{1,*}, Aleksandra Kawala-Sterniuk ² and Dariusz Mikołajewski ³

¹ Institute of Automatic Control and Robotics, Poznan University of Technology, 61-131 Poznan, Poland

² Department of Artificial Intelligence, Faculty of Computer Science and Telecommunications, Wrocław University of Science and Technology, 50-370 Wrocław, Poland; aleksandra.kawala-sterniuk@pwr.edu.pl

³ Faculty of Computer Science, Kazimierz Wielki University, 85-064 Bydgoszcz, Poland; dariusz.mikolajewski@ukw.edu.pl

* Correspondence: aleksandra.swietlicka@put.poznan.pl

Deep learning (DL) has revolutionized natural language processing (NLP), enabling models to learn complex linguistic patterns directly from large-scale text data. Architectures such as recurrent neural networks (RNNs), convolutional neural networks (CNNs), and especially transformers have significantly improved performance in many tasks, such as machine translation, sentiment analysis, and question answering. Recent advances in large, pre-trained language models, such as general pre-trained transformers (GPT), bidirectional encoder representations from transformers (BERT), and T5, have demonstrated strong capabilities in text generation, reasoning, and contextual understanding. Transfer learning and self-supervised learning have become key scientific advances because they reduce reliance on manually annotated datasets.

This Special Issue, “Deep Learning Approaches for Natural Language Processing,” explores current trends, challenges, and developments in the use of deep learning methods for analyzing, understanding, and generating natural language. The collected articles present both innovative methodological solutions and practical applications of these technologies in various fields of science and industry.

Mikołajewska & Masiak (Contribution 1) have shown that DL methods in NLP enable the creation of digital twins of patients in psychiatry and neurological rehabilitation by analyzing unstructured data such as clinical notes, therapeutic conversations, and patient-reported outcomes. Advanced models such as transformer architectures, RNNs, and attention mechanisms can identify linguistic patterns associated with mental disorders, cognitive decline, recovery from aphasia, and other neurological conditions, while simultaneously integrating multimodal data such as speech, gestures, and sensor data for long-term monitoring and predictive analytics. Although these technologies support personalized and real-time clinical decision-making, their implementation requires careful attention to data privacy, fairness, error reduction, and model explainability to ensure the security and reliability of medical applications.

Małolepsza et al. (Contribution 2) provide a comprehensive review of adaptive fuzzy systems based on ordered fuzzy numbers (OFNs), which extend classical fuzzy set theory to better represent uncertainty and variability in complex applications. The study examines and compares the main adaptive approaches, including genetic algorithms, evolutionary programming, reinforcement learning, online adaptation, and learning algorithms, highlighting their advantages, limitations, and practical applications in engineering and social sciences. The analysis indicates that although OFN-based systems show significant potential, further research is needed to address the challenges of computational complexity, scalability, and real-time implementation, while advancing the state of the art in scientific and technological applications.



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Yeo et al.'s study (Contribution 3) addresses the growing use of large language models (LLMs) in medical education by developing an automated tool for assessing nursing students' structured responses based on the SBAR model. The proposed method introduces a three-stage biasing strategy that incorporates reference responses, high-scoring student responses, and weighted noun embeddings to highlight medically relevant terminology and improve similarity assessments between student and expert responses. Results obtained using the Word2Vec, FastText, and Sentence-BERT models show that biasing techniques significantly improve agreement with human ratings, increasing the accuracy, fairness, and consistency of descriptive response assessments in educational environments.

Alsolami & Alrayzah's study (Contribution 4) addresses the limited research on Arabic table-based query answering by introducing Arabic WikiTableQA, the first large-scale non-SQL dataset designed for reasoning from structured Arabic tables. The work highlights key challenges faced by LLMs, including the lack of exemplary datasets, token limitations, and the morphological complexity of Arabic when processing long and complex tables. To overcome these challenges, the authors evaluate methods for direct data entry, sub-table selection, and graph-guided semantic filtering, demonstrating that the graph-guided framework achieves state-of-the-art performance with an accuracy of 74%, significantly outperforming alternative methods.

Buga et al.'s study (Contribution 5) examined the impact of integrating structured building information, such as maintenance schedules, room data, and asset inventories, on the performance of LLMs in facility management applications. Using design science methodology, the authors developed three function call use cases and a modular testing framework to evaluate multiple LLMs, including Gemini, Llama, Qwen, and Mistral, on tasks involving natural language translation to SQL, query execution, and response generation. The results indicate that incorporating structured schema information significantly improves SQL execution accuracy by up to 67%, while also increasing semantic accuracy, contextual relevance, and reducing hallucinations in the generated responses.

Iovane and Iovane's article (Contribution 6) presents a solution to the problem of contemporary generative artificial intelligence (genAI), which often lacks knowledge, contextual awareness, and ethical reasoning. Building on philosophical concepts such as dynamic ontology, intentionality, and dialectical reasoning, they apply multidimensional semantic modeling frameworks, hybrid symbolic–connectionist architectures, layered memory systems, and temporal reasoning to implement advanced interpretable, adaptive, and ethically controlled behavioral intelligence. The article comprises the first step of a broad, six-step research program, presenting basic, formal initial models, a methodological framework, and potential applications of sophimatics. It also outlines applications for the development of post-generative AI systems.

Vahdatian and al.'s study (Contribution 7) presents a "glass-box" recommendation system architecture designed to improve transparency, fairness, and auditability while maintaining high predictive performance in digital recommendation platforms. This framework combines interpretable tree models, sentiment-based natural language processing components, and a Reality Check mechanism that enforces temporal separation and reduces popularity bias, enabling the system to identify hidden growth trends rather than simply reproducing existing popularity patterns. Evaluations on the MovieLens and Amazon Electronics datasets show that the proposed architecture achieves high predictive accuracy and generalizability while integrating management mechanisms such as TreeSHAP explainability, stability analysis, fairness auditing, and dynamic threshold optimization to support reliable and safe-by-design recommendation systems.

Alrasheeda et al. (Contribution 8) present a unified multi-label influence framework, GTHL-Emo, that addresses class imbalance and inter-label dependencies in Arabic emotion

datasets. The proposed solution combines semantic encoding on transformers, structural modeling on GraphSAGE, adaptive hybrid weighted loss, and label correlation differences with KL regularization to access distinctive labels and predictive consistency with a computational burden. Experimental results from three Arabic influence benchmarks using Jaccard, micro-F1, and macro-F1, and ablation studies indicate that graph structure and ranking loss components influence model influence.

Despite these advances, deep learning models still require enormous computational resources, raising concerns about energy consumption, scalability, and unequal access to advanced NLP technologies. Another major issue is the scarcity of high-quality, multilingual, and domain-specific datasets, which limits model performance for low-resource languages and specialized applications [1,2]. Interpretability remains a significant research gap, as many deep neural networks function as black boxes, whose decisions are difficult to explain or verify within eXplainable AI (XAI) [3]. Researchers are also increasingly concerned about fairness and bias, as models trained on large online datasets can reproduce harmful stereotypes or discriminatory linguistic patterns [4]. Recent studies further highlight the challenges of hallucinations, factual inconsistency, and robustness when models encounter ambiguous or adversarial input [5].

Future research areas include the development of more efficient architectures, XAI techniques, reliable evaluation frameworks, and privacy-preserving learning methods [6]. Another promising direction is the integration of symbolic reasoning, multimodal learning [7], and human-centered interaction [8] to create NLP systems that are more robust, adaptable, and aligned with human values.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
BERT	Bidirectional encoder representations from transformers
CNN	Convolutional neural networks
DL	Deep learning
genAI	Generative AI
GPT	General pre-trained transformer
LLM	Large language model
NLP	Natural language processing
OFN	Ordered fuzzy number
RNN	Recurrent neural networks
XAI	eXplainable AI

List of Contributions

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