Journal of Deep Learning

https://journals2.ums.ac.id/index.php/jdl

Visual and Contextual Learning for Deep Learning Education: A Unified Tool for Theory–Practice Integration

Itang Enrico Pradana Mahardhika[1✉], Harun Joko Prayitno[2], Indri[3], Muhammad Ramadhan Fitriyan[4]

[1-3]Faculty of Teacher Training and Education, Universitas Muhammadiyah Surakarta, Indonesia

[4]Faculty of Communication and Informatics, Universitas Muhammadiyah Surakarta, Indonesia

DOI: xxxxx

Received: May 21st, 2025. Revised: June 15th, 2025. Accepted: June 20th, 2025

Available Online: June 30th, 2025. Published Regularly: June, 2025

Abstract

The rapid advancements in artificial intelligence, particularly in deep learning, demand learning methods that are not only theoretical but also applicative and intuitive. This study aims to design and develop an interactive deep learning instructional tool that integrates real-world case studies and dynamic visualizations to enhance users' conceptual understanding and practical skills. The research employs a development methodology with a mixed-methods approach, adopting the ADDIE model and iterative formative evaluation based on Tessmer's framework. The developed tool incorporates three primary case studies: image classification, sentiment analysis, and time-series prediction. Each case study features an interactive interface that allows users to explore data, adjust model parameters, and visualize training processes and results in real time. Formative evaluation results demonstrate the tool's effectiveness in improving learning engagement, understanding of deep learning model mechanisms, and motivation to explore the topic further. These findings underscore the significance of experiential and visualization-based approaches in cutting-edge technology education while contributing to the development of adaptive AI-based learning media.

Keywords: deep learning, experiential learning, image classification, instructional tool, interactive visualization, natural language processing

✉***Corresponding Author:***

Itang Enrico Pradana Mahardhika, Faculty of Teacher Training and Education, Universitas Muhammadiyah Surakarta

Email: q100249001@student.ums.ac.id

1. Introduction

The current advancement of digital technology, particularly in artificial intelligence (AI), has progressed rapidly (Baskara et al., 2023). One of the main pillars of modern AI transformation is deep learning, which excels in processing complex information and automatically recognizing abstract patterns. This advantage has driven breakthroughs in computer vision, natural language processing, and recommendation systems (LeCun et al, 2015). However, the complexity of algorithms and high mathematical abstraction often pose significant barriers, especially for novice learners.

The primary challenge lies in the limited availability of learning approaches that can intuitively and practically bridge theory with implementation. Conventional methods that heavily emphasize theoretical explanations and mathematical formulas often fail to provide a comprehensive understanding of how deep learning models function in real-world applications (Goodfellow et al, 2016). Consequently, a gap emerges between conceptual understanding and implementation skills, hindering the holistic internalization of knowledge (Chollet, 2018; Zhang et al., 2021).

Several studies indicate that beginners in this field frequently struggle to comprehend how deep learning models process data and generalize, particularly when learning is not supported by visual and applied approaches (Kim et al, 2018). This underscores the urgency of developing exploratory and experiential learning methods to more effectively connect theory and practice (Goodfellow et al, 2016).

One promising approach gaining attention is the integration of practical case studies with interactive visualizations within a unified learning platform. Case studies enable students to understand the application of deep learning models in real-world contexts, such as data processing, prediction, and result evaluation (Kolodner, 1993). Meanwhile, interactive visualizations simplify complex computational processes through easily interpretable graphical displays and allow direct exploration of model parameters (Tufte, 2001). This combination not only enhances conceptual understanding but also increases student engagement and interest in learning.

The uniqueness of the proposed approach in this study lies in the integration of these two methods into a single, cohesive learning tool. Most current deep learning teaching methods still separate theoretical aspects, practical exercises, and exploratory visualizations. However, prior research has demonstrated that interactive visualizations significantly strengthen comprehension of complex AI concepts (Kahng et al., 2018), while case studies provide the much-needed real-world context for experiential learning (Kolodner, 1993). This integration is also believed to accommodate diverse learning styles from visual to kinesthetic as well as varying cognitive abilities among students (Chen et al., 2020).

This study aims to design and develop a deep learning instructional tool that combines practical case studies and interactive visualizations into a unified platform. The tool is designed to support self-directed learning as well as complement formal instructional activities. By providing real-world contexts and visual exploration spaces, this approach is expected to bridge the gap between theory and practice while enhancing students' overall learning experience. This aligns with the principles of experiential learning, which emphasize active engagement in the learning process (Kolb, 1984), and is relevant for reinforcing AI-based understanding, which has been proven effective through visualization (Liu et al., 2017). Within formal and non-formal education frameworks, this also aligns with educational goals of fostering meaningful interactive processes between educators and learners (Fata et al., 2021; Jayanti et al., 2022).

2. Method

This study adopts a mixed-methods research approach with a development research oriented orientation combined with iterative formative evaluation. The main focus of this research lies in the design and implementation of a deep learning instructional tool based on case studies supported by interactive visualizations. The entire development process was conducted iteratively to enable early detection of design weaknesses, obtain continuous user feedback, and gradually refine the product using the evaluative framework proposed by Tessmer (1993).

A. Learning Tool Development Stages

The development of the instructional tool follows the ADDIE framework (Analysis, Design, Development, Implementation, Evaluation), applied in a flexible and iterative manner (Branch, 2009). Each stage is explained as follows:

1) Analysis

This initial stage includes identifying user needs related to deep learning instruction, mapping difficult concepts that require visualization support, and selecting relevant and contextual case studies. Data collection was carried out through literature studies, brief interviews with potential users (such as university students or novice practitioners), and curriculum and existing learning materials analysis.

2) Design

Based on findings from the analysis phase, the architecture of the instructional system was designed, including user interface (UI) design, types and forms of interactive visualizations to support understanding, learning flow, and user interaction mechanisms. These designs were presented in the form of mockups and storyboards which served as the basis for development.

3) Development

The mockups and storyboards were then implemented into a functional prototype of the instructional tool. This process included selecting the appropriate platform or technological framework, creating visualizations using suitable graphic libraries, and integrating case studies into the tool. Emphasis was placed on interactivity and accessibility for beginner users.

4) Implementation

The initial prototype was tested with a small group of target users to evaluate functionality, visualization clarity, and learning flow. This trial was systematically documented to capture user interaction patterns, emerging obstacles, and responses to the system's core features.

5) Evaluation

Evaluation was carried out formatively and iteratively at each stage, especially after the initial trial. Evaluation techniques included direct observation, feedback questionnaires (assessing usability, visualization effectiveness, and conceptual understanding), and in-depth interviews to explore learning experiences qualitatively. The findings were used to refine the product through continuous iteration.

B. Data Collection and Analysis

Data were collected and analyzed using a triangulation approach as follows:

1) Quantitative data were obtained through questionnaires and analyzed using descriptive statistics (mean, standard deviation, percentage) to identify general tendencies in users' perceptions of the system's effectiveness.
2) Qualitative data were derived from field observations and semi-structured interviews, then analyzed using thematic analysis techniques to identify narrative patterns, key themes, and conceptual aspects that deepen understanding of the tool's impact on the learning process.

The results from both types of analysis were synthesized to produce a comprehensive evaluation covering the strengths, limitations, and potential areas for further development of the learning tool.

C. Research Participants

Participants in this study consisted of individuals with an interest or background in deep learning education at beginner to intermediate levels. The sample was selected purposively to ensure diversity in terms of academic background, technical experience, and initial understanding of the topic. The number of participants in the initial trial was determined based on the adequacy principle, which emphasizes the representativeness of qualitative findings and the validity of the feedback obtained, without compromising the efficiency of the development process.

3. Results and Discussion

After undergoing the development process based on the ADDIE model and iterative formative evaluation, an integrative deep learning instructional tool was successfully designed and implemented. The following section presents a detailed description of the structure, features, and case studies integrated into the tool as the main outcome of this research.

A. Description of the Interactive Deep Learning Learning Tool:

The curriculum plays an essential role through learning tools that serve as structured plans for learning activities, representing the process of acquiring knowledge and experience through a sequence of learning events (Agustina et al., 2025; Setyaningsih et al., 2024). The developed deep learning instructional tool in this study is designed with an integrative approach that combines theory, practice, and visualization. A key feature of this tool is the use of real-world case studies drawn from various application domains. As such, the learning process is no longer abstract or detached from reality but is grounded in concrete and relevant contexts. This approach is believed to enhance comprehension and knowledge retention, as users can relate the concepts learned to real-world phenomena.

1. Image Classification

One of the core case studies integrated into the instructional tool is image classification, which is widely regarded as an ideal entry point for understanding basic concepts in deep learning. This case study was chosen for its intuitive and visual characteristics, which facilitate learners in observing how algorithms learn from data. The system is designed to demonstrate the entire machine learning workflow from image preprocessing, training a model using convolutional architectures, to evaluating classification accuracy. Users can interact directly with various model parameters, such as the number of layers, convolutional filter sizes, and activation functions, and observe the effects of these changes on model performance in real-time. An example classification between images of cats and dogs is used for illustration due to its everyday relevance and its ability to represent sufficient visual complexity to build both conceptual and technical intuition. Thus, this approach not only introduces the basic concept of classification but also promotes an applied understanding of the internal mechanisms of neural networks (Smith et al., 2023).

Figure 1. Deep Learning Learning Practice

Figure 2. Multidirectional Communication in Deep Learning

Figure 1 displays visual documentation of learning practices using the interactive deep learning tool. In this image, participants are seen exploring various model parameters such as layer count and filter size while observing model performance changes in real time through graphical visualizations of accuracy and loss. This representation reflects the application of experiential learning principles, where learners actively engage in exploratory and reflective processes based on visual feedback. Meanwhile, Figure 2 illustrates a multidirectional communication architecture between users and the system. This diagram emphasizes that the tool is not merely instructional in a one-way manner but enables dynamic interaction that facilitates simulation-based learning (Hanifah et al., 2024). Each user action, such as resetting parameters or selecting input data, automatically triggers a new relevant visualization, creating a responsive and contextual learning experience. Together, these figures demonstrate the advantages of the interactive approach in building both conceptual and applied understanding in deep learning education.

2. Sentiment Analysis

The second case study in the instructional tool focuses on sentiment analysis, one of the main applications of deep learning in the field of Natural Language Processing (NLP). This case study was designed to introduce learners to the computational workflow of natural language processing, from text tokenization and conversion to numerical representations (such as word embeddings), to using neural network models to classify sentiment into positive, negative, or neutral categories.

This topic was selected not only for its industrial relevance such as analyzing customer reviews or social media responses but also for its high educational value in understanding the complexity of human language in the context of machine processing (Medhat et al, 2014; Zhang et al, 2018; Zhang et al., 2024).

In implementation, users are introduced to an interactive interface that allows them to input raw text, configure model parameters (e.g., number of LSTM units, dropout rate), and observe classification results and confidence scores visually. The visualizations are accompanied by explanatory graphics and diagrams that help users trace how the model makes decisions based on identified linguistic patterns. This experience-based approach has been proven to enhance knowledge retention and cognitive engagement, as users do not merely learn theory but also observe how NLP models work end-to-end (Kolb, 1984; Prince & Felder, 2006).

Table 1. Example of Sentiment Classification Results

Input Text	Predicted Label	Confidence Score
"This product is very satisfying and of high quality."	Positive	0.92
"Customer service is poor and unresponsive."	Negative	0.89
"The experience was average, nothing too special."	Neutral	0.77

Table 1 displays the sentiment classification results for three different input texts. The system accurately distinguishes emotional contexts, as indicated by the high confidence scores (above 0.75). These scores reflect the model's level of certainty in its predictions. Higher values indicate that the model has effectively learned to identify affective patterns in text, helping users understand how textual data is processed into meaningful output.

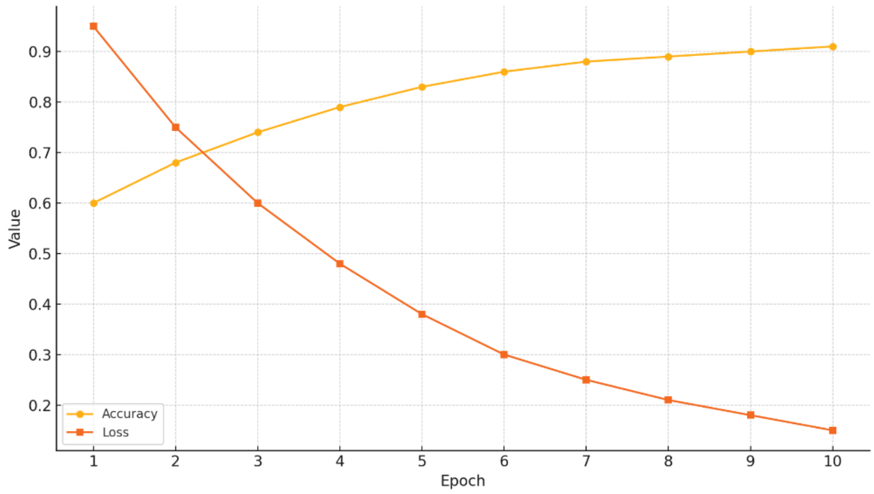

Figure 3. Training Accuracy and Loss of LSTM Sentiment Model

Figure 3 presents the performance of the LSTM model in sentiment classification tasks over 10 epochs. Accuracy consistently increases, while the loss value drops sharply in the initial epochs before stabilizing indicating effective learning from the training data. Real-time visualizations such as this enable users to understand how model parameters and data influence the learning process. These charts are highly effective in bridging abstract understanding with the inner workings of complex model training.

3. Time Series Prediction

The third case study addresses time series forecasting, a crucial deep learning application for processing temporal data. This approach enables models to learn patterns from historical data and use them to predict future values. It is highly relevant in areas such as stock price prediction, energy demand forecasting, or weather forecasting (Davis & Wilson, 2024).

In this case study, users are introduced to neural network architectures specifically designed for sequential data, such as Recurrent Neural Network (RNN) and Transformers. Users can explore how models recognize short- and long-term dependencies in data and how predictions are made based on prior patterns. The visualization of predicted results compared to actual data helps users understand the model's accuracy and identify potential prediction errors.

The tool also features an interactive interface for configuring essential parameters like the number of RNN units, window size, and number of epochs. This extends the learning scope from static classification to dynamic forecasting, requiring understanding of temporal structures.

The formative evaluation results indicate that a case study and interactive visualization-based deep learning approach shows potential in addressing challenges of comprehending complex concepts. Interactive visualizations successfully transform abstract processes such as model learning mechanisms and data processing workflows into more accessible visual representations. These findings align with constructivist principles emphasizing that understanding is constructed through active experience and interaction with learning materials (Jonassen, 1991; Prayitno et al., 2024). Within modern learning technology contexts, visualizations function as cognitive tools that facilitate information structuring, simplify inference-making, and reduce cognitive load when studying complex topics (Liu et al., 2017; Kahng et al., 2018).

The study reveals that significant improvements in conceptual understanding, learning engagement, and student-reported motivation can be attributed to the interactive and visual characteristics of the developed instructional tool. The system design, which enables learners to directly modify model parameters and immediately observe effects through dynamic visual representations, appears to create more immersive learning experiences. This mechanism not only reinforces learners' sense of control and agency but also facilitates intuitive understanding of cause-effect relationships in deep learning models. Furthermore, the inclusion of real-world case studies successfully bridges the gap between abstract theory and practical implementation, rendering the learning process more contextual, applicable, and intrinsically engaging.

Holistically, these findings substantiate the proposition that a deep learning instructional approach integrating concrete case studies with interactive visualizations represents a potential educational breakthrough. This approach effectively lowers barriers to entry for learning complex deep learning concepts, particularly for secondary-level learners. Future development prospects encompass two strategic directions: (1) expanding the variety and depth of case studies to cover a broader application spectrum, and (2) refining visualization techniques to display more granular and informative computational processes. Advancements in both aspects are anticipated to exponentially enhance the tool's pedagogical effectiveness.

These findings are empirically supported by prior research affirming visualization's critical role in learning complex computer science and artificial intelligence concepts (Byron & Wattenberg, 2008; Hohne & Kröger, 2006). Well-designed case studies act as learning catalysts by providing authentic application contexts, enabling concept internalization through direct experience a principle foundational to Kolb (1984) experiential learning theory. Specifically, the synergy between visual scaffolding and case-based learning optimizes knowledge transfer and long-term concept retention.

The evaluation identified several aspects requiring further refinement for tool optimization. First, case study diversification is needed by expanding the difficulty spectrum (from basic to advanced levels) and application domain coverage (e.g., including healthcare, automotive, or finance fields) to accommodate more heterogeneous learner needs. Second, more advanced visualization techniques should be developed to represent more complex deep learning concepts, such as: (1) multidimensional feature space representations, (2) visualizations of data transformations in hidden layers, and (3) interactive diagrams showing gradient propagation during training. Refinements in both aspects are expected to enhance the tool's adaptability to various learning styles while deepening users' conceptual understanding of deep learning's internal mechanisms that often function as black boxes.

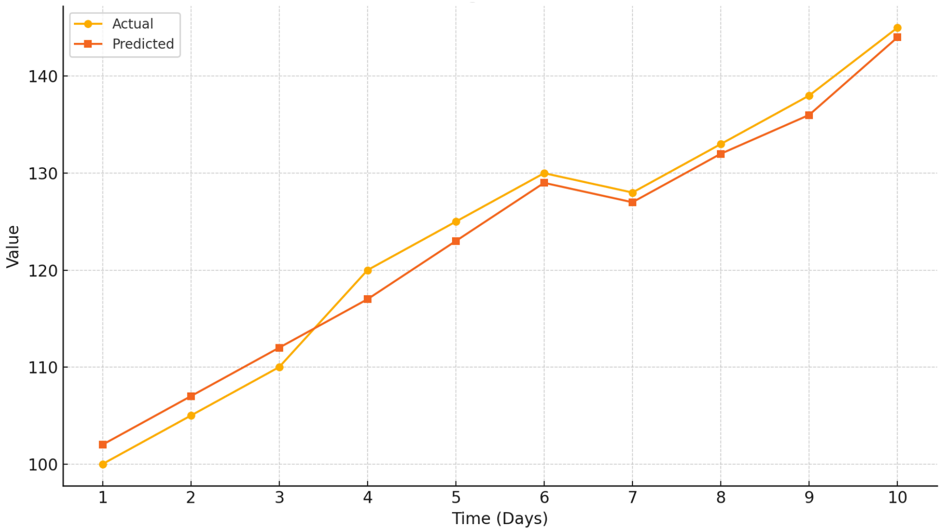

Figure 2. Time Series Forecasting: Actual vs Predicted Values

Figure 2 presents a comparative visualization of actual versus predicted values over a 10-day period within the time series prediction case study. The orange curve represents actual values, while the blue curve indicates predictions generated by the deep learning model post-training. Overall, both curves exhibit striking alignment with closely matched rise-and-fall trends, indicating that the model has successfully learned the temporal structure embedded in historical data.

This pattern congruence demonstrates the model's capacity to capture both short-term and long-term dependencies in sequential data a core challenge in time series forecasting. The high prediction accuracy assures users that the model not only functions mathematically but also generalizes complex data behaviors effectively. In educational contexts, such visualizations play a critical role by enabling users to directly observe how parameter adjustments impact predictive performance (Adhantoro et al., 2025).

Furthermore, this graph serves as a reflective tool for model evaluation, allowing users to readily identify deviation points or anomalies between predictions and actual values. Through this experience, learners not only comprehend model mechanics but also develop analytical intuition for interpreting predictions in relation to real-world phenomena. Consequently, this visualization is integral to an interactive learning approach emphasizing simultaneous visual exploration and conceptual understanding.

Formative evaluation results indicate that the case-based and interactive visualization approach to deep learning instruction has the potential to overcome challenges related to understanding complex concepts. Interactive visualizations have successfully transformed abstract processes such as model learning mechanisms and data processing workflows into visual representations that are more accessible and easier to comprehend. These findings are in line with the principles of constructivism, which emphasize that understanding is built through active experience and interaction with learning materials (Jonassen, 1991; Andyani et al., 2024). In the context of modern learning technologies, visualization serves as a cognitive tool that facilitates the structuring of information, supports inference, and reduces cognitive load when studying complex topics (Liu et al., 2017; Kahng et al., 2018).

The research findings reveal that significant improvements in conceptual understanding, learning engagement, and learner motivation as reported by students can be attributed to the interactive and visual nature of the developed learning tool. The system's design, which allows learners to directly modify various model parameters and immediately observe the effects of those changes through dynamic visual representations, appears to create a more immersive learning experience. This mechanism not only enhances learners' sense of control and agency, but also facilitates an intuitive understanding of cause-and-effect relationships within deep learning models. Furthermore, the inclusion of real-world case studies successfully bridges the gap between abstract theory and practical implementation, making the learning process more contextual, applicable, and intrinsically engaging.

Holistically, the study's findings reinforce the proposition that a deep learning instructional approach that integrates concrete case studies with interactive visualizations represents a promising educational breakthrough (Zhang et al., 2024). This approach effectively lowers the barriers to entry in learning complex deep learning concepts, particularly for learners at the secondary education level. Future development directions may focus on two strategic areas: (1) expanding the variety and depth of case studies to encompass a broader spectrum of applications, and (2) enhancing visualization techniques to represent computational processes in a more granular and informative manner. Improvements in these two areas are expected to significantly increase the pedagogical effectiveness of the tool.

These findings are supported by empirical evidence from prior studies emphasizing the crucial role of visualization in learning complex concepts in computer science and artificial intelligence (Byron & Wattenberg, 2008; Hohne & Kroger, 2006). Well-designed case studies function as learning catalysts by providing authentic application contexts that enable learners to internalize concepts through direct experience a principle that lies at the core of Kolb (1984) experiential learning theory. In particular, the combination of visual scaffolding and case-based instruction creates a pedagogical synergy that optimizes knowledge transfer and long-term conceptual retention.

The evaluation also identified several aspects that require further refinement to optimize the learning tool. First, case study diversification is needed by broadening the range of difficulty (from basic to advanced) and expanding the domain coverage (e.g., healthcare, automotive, or finance) to accommodate the needs of more heterogeneous learners (Adhantoro et al., 2025). Second, the development of more advanced visualization techniques should be considered to represent more complex deep learning concepts, such as: (1) multidimensional feature space representations, (2) data transformation visualizations across hidden layers, and (3) interactive diagrams showing gradient propagation during training. Refinements in these two areas are expected to improve the tool's adaptability to various learning styles while deepening users' conceptual understanding of deep learning's internal mechanisms, which are often perceived as a black box.

4. Conclusion

This study successfully developed an interactive deep learning instructional tool based on real-world case studies and dynamic visualizations, designed to bridge the gap between theoretical understanding and practical skills in learning deep learning technologies. The tool comprises three primary case studies image classification, sentiment analysis, and time series prediction each representing deep learning applications in different domains, namely computer vision, natural language processing, and temporal data.

Formative evaluation results show that the experiential learning approach implemented through interactive visualization and direct model parameter configuration effectively enhances users' conceptual understanding, learning motivation, and cognitive engagement. Moreover, the selection of contextual case studies has proven effective in linking abstract concepts to real-world applications, thereby strengthening knowledge transfer.

Therefore, the tool has strong potential to be used both as a self-directed learning medium and as part of the formal curriculum in information technology education. Future development may focus on expanding the variety of case studies and improving the adaptability of the system to accommodate users with varying levels of proficiency.

5. References

Adhantoro, M. S., Anif, S., Sutopo, A., Umardhani, N. S. Z., Ulya, W., & Sopianti, H. (2025). Pelatihan Desain Digital Berbasis Canva bagi Anak Migran Indonesia di SB Kulim, Penang: Upaya Peningkatan Literasi Teknologi dan Rasa Percaya Diri. *Jurnal Ilmiah Kampus Mengajar*, 95-110.

Adhantoro, M. S., Gunawan, D., Prayitno, H. J., Riyanti, R. F., Purnomo, E., & Jufriansah, A. (2025). Strategic technological innovation through ChatMu: transforming information accessibility in Muhammadiyah. *Frontiers in Artificial Intelligence*, *8*, 1446590.

Agustina, P., Astuti, R., & Agustina, L. (2025). Keterampilan Mahasiswa Calon Guru Biologi dalam Menerapkan Kurikulum Merdeka Berdasarkan Pengembangan Perangkat Pembelajaran. Proceeding Biology Education Conference, 1, 37–42.

Andyani, R. A., Shobri, M. Q., Baihaqi, M. A., Al-Kubro, P. B., & Adhantoro, M. S. (2024). Aplikasi Metode Ward dengan Berbagai Pengukuran Jarak (Studi Kasus: Klasifikasi Tingkat Perekonomian di Indonesia). *Jurnal Ilmiah Kampus Mengajar*, 177-190.

Baskara, F. R., Puri, A. D., & Wardhani, A. R. (2023). ChatGPT and the Pedagogical Challenge: Unveiling the Impact on Early-Career Academics in Higher Education. Indonesian Journal on Learning and Advanced Education (IJOLAE), 5(3), 311–322. https://doi.org/10.23917/ijolae.v5i3.22966

Branch, R. M. (2009). Instructional design: The ADDIE approach. Springer Science & Business Media.

Byron, L., & Wattenberg, M. (2008). Stacked Graphs–Geometry & Semantics. *IEEE Transactions on Visualization and Computer Graphics*, 14(6), 1245-1252.

Chen, W., Saad, F., Yuille, A. L., & Xing, E. P. (2020). Interactive Machine Learning Education: A Visual Analytics Approach. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–12. https://doi.org/10.1145/3313831.3376486

Chollet, F. (2018). *Deep Learning with Python.* Manning Publications.

https://www.manning.com/books/deep-learning-with-python

Davis, L., & Wilson, S. (2024). *Teaching Time Series Prediction with Deep learning: Practical Case Studies*. International Conference on *Deep learning* for Education, Proceedings

Fata, Z., Su'ad, S., & Murtono, M. (2021). Pola Pembelajaran Guru pada Masa Pandemi Corona (Covid-19) SD Negeri Kramat 3 Kecamatan Dempet Kabupaten Demak. *Profetika: Jurnal Studi Islam*, 22(1), 109–118. https://doi.org/10.23917/profetika.v22i1.14769

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT press.

Hanifah, D., Prayitno, H. J., Adhantoro, M. S., Purnomo, E., Pradana, F. G., & Kurniaji, G. T. (2024, July). Utilization of" Wordwall" Media in Increasing Digital Literacy in Third-grade Students at Pajang III State Elementary School. In *International Conference on Education for All* (Vol. 2, No. 1, pp. 165-179).

Herreid, C. F. (2011). Case study teaching. *New Directions for Teaching and Learning, 2011*(128), 31–40. https://doi.org/10.1002/tl.465

Hohne, K. H., & Kroger, W. (2006). Visualization in Medicine An Overview. *IEEE Transactions on Visualization and Computer Graphics*, 12(5), 780-794.

Jayanti, I. T., Cahyo, A. N., Setyaningsih, E., Purnomo, E., Winarti, A., & Mawardi, M. (2022). Penguatan Pendidikan Karakter Religius di TPA (Taman Pendidikan Al-Qur'an) Nurul Yaqin Desa Jagoan. *Buletin KKN Pendidikan*, 4(1), 69–79. https://doi.org/10.23917/bkkndik.v4i1.19184

Jonassen, D. H. (1991). Objectivism Versus Constructivism: Do We Need A New Philosophical Paradigm? *Educational Technology Research and Development, 39*(3), 5–14. https://doi.org/10.1007/BF02296434

Kahng, M., Andrews, P. Y., Kalro, A., & Chau, D. H. (2018). ActiVis: Visual Exploration of Industry-Scale Deep Neural Network Models. *IEEE Transactions on Visualization and Computer Graphics, 24*(1), 88–97. https://doi.org/10.1109/TVCG.2017.2744878

Kim, T., Shafto, P., & Tenenbaum, J. B. (2018). Teaching Machines Human Strategies for Learning. *Trends in Cognitive Sciences, 22*(8), 643–654. https://doi.org/10.1016/j.tics.2018.05.006

Kolb, D. A. (1984). *Experiential learning: Experience as the Source of Learning and Development*. Prentice Hall.

Kolodner, J. L. (1993). *Case-Based Reasoning*. Morgan Kaufmann.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). *Deep Learning*. Nature, 521(7553), 436-444.

Liu, S., Maljovec, D., Wang, B., Bremer, P. T., & Pascucci, V. (2017). Visualizing High-Dimensional Data: Advances in the Past Decade. *IEEE Transactions on Visualization and Computer Graphics, 23*(3), 1249–1268. https://doi.org/10.1109/TVCG.2016.2640960

Medhat, W., Hassan, A., & Korashy, H. (2014). Sentiment analysis algorithms and applications: A survey. *Ain Shams Engineering Journal, 5*(4), 1093–1113. https://doi.org/10.1016/j.asej.2014.04.011

Prayitno, H. J., Fitriany, D. N., Purnomo, E., Andyani, R. A., Adhantoro, M. S., Kurniaji, G. T., & Jufriansah, A. (2024, July). The Use of Audiovisual Learning Media to Enhance Digital Literacy Competence in Indonesian Language Learning Among Fifth-Grade Students at SDN 02 Baleharjo. In *International Conference on Education for All* (Vol. 2, No. 1, pp. 71-87).

Prince, M., & Felder, R. (2006). Inductive Teaching and Learning Methods: Definitions, Comparisons, and Research Bases. *Journal of Engineering Education, 95*(2), 123–138.

https://doi.org/10.1002/j.2168-9830.2006.tb00884.x

Setyaningsih, N., Khotimah, R. P., Jannati, A. A., & Davi, D. R. (2024). Pendampingan Penyusunan Perangkat Pembelajaran berbasis Problem Based Learning untuk Meningkatkan Komunikasi Matematika Siswa. *PengabdianMu: Jurnal Ilmiah Pengabdian Kepada Masyarakat*, 9(7), 1247–1252.

Smith, J., Brown, K., & Davis, L. (2023). *Visual Case Studies in Deep learning Education*. *Journal of Educational Technology*.

Tessmer, M. (1993). *Planning and Conducting Formative Evaluations: Improving the Quality of Education and Training*. Kogan Page.

Tufte, E. R. (2001). *The Visual Display of Quantitative Information*. Graphics press.

Zhang, L., Wang, S., & Liu, B. (2018). Deep Learning for Sentiment Analysis: A Survey. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 8*(4), e1253. https://doi.org/10.1002/widm.1253

Zhang, Q., Yang, L., & Wang, Y. (2021). Bridging the Gap between Theory and Practice in Deep Learning Education: A Case-Based Pedagogical Framework. *IEEE Transactions on Education, 64*(2), 111–120. https://doi.org/10.1109/TE.2021.3059432

Zhang, Y., Chen, H., & Liu, D. (2024). *Integrating NLP Case Studies into Deep learning Curricula*. *Journal of Natural Language Processing in Education.*