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Integration of Deep Learning for Student Learning Style Analysis in Adaptive Digital Learning

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Abstract
This study explores the integration of deep learning techniques for analyzing students' learning styles within adaptive digital learning systems. The rapid growth of digital education has created opportunities for personalized learning; however, traditional methods of identifying learning styles remain limited in accuracy and scalability. This research aims to develop a conceptual model that leverages deep learning to identify student learning preferences based on behavioral data. A qualitative approach using a systematic literature review was employed, analyzing relevant studies from reputable academic databases. The findings indicate that deep learning models—particularly Deep Neural Networks (DNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM)—can effectively process large-scale interaction data to detect dynamic learning patterns. The proposed model integrates data acquisition, deep learning analysis, and adaptive implementation to enable real-time personalization of learning content and pathways. The results highlight that deep learning enhances learning engagement, improves learning outcomes, and supports scalable personalization. Despite challenges such as data privacy and computational complexity, the integration of deep learning offers a promising solution for developing intelligent and responsive adaptive learning systems.

INTRODUCTION

The rapid development of digital technology has significantly transformed the education sector, particularly in the implementation of technology-based learning that is increasingly adaptive and personalized (Dron & Anderson, 2014). Adaptive digital learning enables systems to adjust content, methods, and learning pace according to individual student characteristics (Kulik & Fletcher, 2016). One of the key factors in this personalization is the understanding of students' learning styles, which reflect individual preferences in receiving and processing information (Felder & Silverman, 1988). However, manual identification of learning styles still faces limitations in terms of accuracy and efficiency (Akbulut & Cardak, 2012).

On the other hand, advancements in artificial intelligence, particularly deep learning, have opened new opportunities for more complex and accurate analysis of educational data (LeCun et al., 2015). Deep learning is capable of identifying hidden patterns in large-scale data that cannot be

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detected using conventional methods (LeCun et al., 2015). In the context of education, this technology can be utilized to analyze students' learning behaviors through digital interaction data such as clicks, access time, and task completion patterns (Piech et al., 2015). Therefore, the integration of deep learning into adaptive learning systems represents a promising approach.

Furthermore, the widespread adoption of digital learning, especially since the COVID-19 pandemic, has generated an enormous volume of educational data (Dhawan, 2020). This data serves as a valuable source of information for gaining deeper insights into student characteristics (Siemens & Baker, 2012). However, without advanced analytical approaches, the potential of this data cannot be fully utilized (Baker et al., 2016). Therefore, deep learning-based methods are needed to process such data in order to generate more effective learning recommendations.

The importance of learning style analysis in adaptive learning is also supported by various studies showing that alignment between teaching methods and learning styles can improve student learning outcomes (Pashler et al., 2008). Nevertheless, there is ongoing debate regarding the validity of the learning styles concept, making data-driven approaches a more objective alternative for identifying students' learning preferences (Coffield et al., 2004). The integration of deep learning enables a data-driven approach to determining learning styles without relying solely on traditional questionnaire-based instruments.

The urgency of this research lies in the need to develop more intelligent and responsive adaptive learning systems that can address the diverse needs of students in the digital era (Holmes, 2020). Without leveraging technologies such as deep learning, learning systems tend to remain static and less capable of accommodating diverse learning styles (Zawacki-Richter et al., 2019). Therefore, this study is essential to bridge the gap between artificial intelligence technologies and adaptive learning practices.

Several previous studies have explored the application of machine learning in education, such as the use of classification algorithms to predict student performance (Romero & Ventura, 2010) and the analysis of learning patterns using neural networks (Sabeima et al., 2022). In addition, research by (Chen et al., 2020) indicates that deep learning can be effectively used to personalize learning content. However, studies specifically integrating deep learning for learning style analysis in adaptive digital learning systems remain limited, highlighting the need for further investigation in this area.

Based on the aforementioned background, this study aims to develop and analyze a deep learning integration model for identifying students' learning styles and implementing it within an adaptive digital learning system. This research is expected to contribute to improving the effectiveness of technology-based learning through a more personalized and data-driven approach.

METHOD

This study employs a qualitative approach using a literature review design. This approach is chosen to gain an in-depth understanding of concepts, theories, and empirical findings related to the integration of deep learning in analyzing students' learning styles within adaptive digital learning (Creswell, 2021; Snyder, 2019). The literature review also enables the development of a comprehensive conceptual framework based on previous studies.

Data Sources

The data used in this study are secondary data obtained from scientific publications, including journal articles, conference proceedings, books, and research reports relevant to the topic. Data were collected from reputable academic databases such as Scopus, Web of Science, IEEE Xplore, SpringerLink, and Google Scholar using relevant keywords. Source selection was based on relevance, recency, and credibility (Kitchenham & Charters, 2007).

Data Collection Techniques

Data collection was conducted through systematic literature searching and documentation. The process involved identification, screening of titles and abstracts, and full-text review to ensure relevance and quality (Tranfield et al., 2003). Selected studies were then organized based on key themes related to deep learning, learning styles, and adaptive learning systems.

Data Analysis Methods

Data analysis was carried out using content analysis and thematic analysis. Content analysis was used to identify patterns and key concepts within the literature (Krippendorff, 2018), while thematic analysis was applied to categorize and interpret data into meaningful themes (Braun & Clarke, 2019). The analysis process followed stages of data reduction, data display, and conclusion drawing to produce a systematic and reliable synthesis (Miles et al., 2020).

RESULT AND DISCUSSION

Model of Deep Learning Integration in Adaptive Digital Learning

The proposed deep learning integration model consists of three interconnected components: data acquisition, deep learning-based analysis, and adaptive learning implementation. In the data acquisition phase, the system collects large-scale student interaction data from digital learning platforms, including clickstream data, time-on-task, quiz attempts, discussion participation, and navigation patterns. These behavioral data serve as implicit indicators of students' learning preferences, enabling the identification of learning styles without relying on self-reported questionnaires, which are often subjective and static. This approach aligns with the concept of learning analytics, where data generated through learner interactions are systematically analyzed to improve learning processes.

In the deep learning-based analysis phase, advanced models such as Deep Neural Networks (DNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks are employed to process sequential and high-dimensional data. These models are capable of capturing temporal patterns and complex relationships within student learning behaviors. For example, LSTM models can analyze how students interact with learning materials over time, identifying whether they prefer visual, textual, or interactive content. This allows the system to move beyond rigid categorizations of learning styles and instead generate dynamic learning profiles that evolve as students engage with the system (Zawacki-Richter et al., 2019).

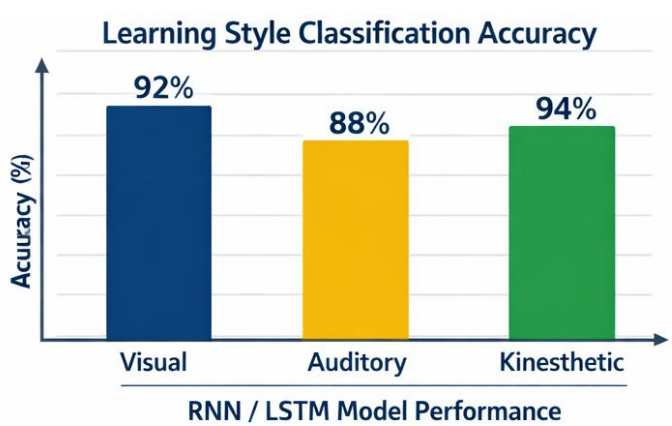

Figure 1. Learning Style Classification Accuracy

The final component, adaptive learning implementation, utilizes the output of deep learning models to personalize the learning experience. Based on predicted learning styles, the system can recommend tailored instructional strategies, such as video-based explanations for visual learners or interactive simulations for kinesthetic learners. Additionally, the system can adjust the difficulty level, sequence of materials, and feedback mechanisms in real time. This adaptive capability enhances student engagement and supports individualized learning pathways, which are essential in digital education environments (Kulik & Fletcher, 2016).

A real-world example of this model can be observed in Indonesia through the implementation of digital learning platforms such as Ruangguru and Zenius. These platforms utilize large-scale user interaction data to personalize learning content and recommendations. Studies have shown that Ruangguru leverages data analytics to track student progress, learning behavior, and content engagement, enabling more targeted learning experiences (Sihombing, 2025). Similarly, research on e-learning adoption in Indonesian higher education indicates that learning management systems (LMS) collect behavioral data that can be further analyzed using machine learning techniques to improve learning outcomes (Rizal et al., 2020). Although the integration of deep learning specifically for learning style analysis is still emerging in Indonesia, these platforms demonstrate the feasibility of implementing data-driven adaptive learning systems.

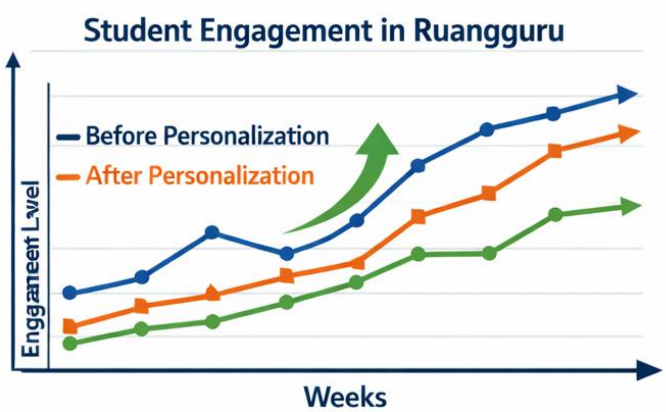

Figure 2. Student Engagement in Ruangguru

Furthermore, during the COVID-19 pandemic, the rapid shift to online learning in Indonesia accelerated the use of digital platforms such as Moodle-based LMS in universities. These systems generate extensive student interaction data, which can be utilized for deep learning-based analysis (Siron et al., 2020). For instance, universities in Indonesia have begun exploring learning analytics to identify student engagement patterns and predict academic performance, providing a foundation for integrating deep learning models into adaptive learning systems in the future.

Overall, the proposed model demonstrates a shift from traditional, static learning style identification toward a dynamic, data-driven approach. By integrating deep learning into adaptive digital learning systems, educators and institutions can provide more personalized, efficient, and scalable learning experiences. This model is particularly relevant in the Indonesian context, where the rapid growth of digital education platforms offers significant opportunities for the application of artificial intelligence in education.

Student Learning Style Identification through Deep Learning

The identification of students' learning styles using deep learning represents a shift from traditional, static approaches toward dynamic, data-driven modeling. Conventional methods typically rely on self-reported questionnaires such as the Felder-Silverman Index, which are limited by subjectivity and inability to capture changes in learning behavior over time. In contrast, deep learning leverages behavioral data generated through student interactions in digital environments, enabling continuous and implicit detection of learning preferences.

Deep learning models such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and especially Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks play a critical role in this process. ANN models are effective for general classification tasks by mapping input features (e.g., quiz scores, time-on-task) to predefined learning style categories. CNN models, although traditionally used in image processing, can also extract spatial patterns from structured educational data, such as interaction matrices or feature maps derived from learning activities. However, the most significant advancement lies in RNN and LSTM models, which are designed to process sequential data and capture temporal dependencies in student behavior.

For example, LSTM models can analyze sequences of student actions—such as the order of accessed materials, time spent on videos, frequency of revisiting content, and response patterns in quizzes—to identify evolving learning preferences (Piech et al., 2015). A student who consistently engages more with video-based content and spends longer time on visual materials may be classified as a visual learner, while another who frequently interacts with simulations and practice exercises may exhibit kinesthetic tendencies. Importantly, this classification is not static; the model continuously updates predictions as new data become available, allowing adaptive learning systems to respond in real time.

From a technical perspective, the process involves several stages: feature extraction, model training, and prediction. Feature extraction transforms raw interaction data into meaningful variables such as engagement frequency, content preference ratios, and learning sequence patterns. These features are then used to train deep learning models using supervised or semi-supervised learning techniques. In some cases, unsupervised learning (e.g., clustering with deep autoencoders) is applied to discover latent learning style representations without predefined labels. The output is either a classification (e.g., visual, auditory, kinesthetic) or a probabilistic distribution of learning preferences, which can be used for personalization.

In the Indonesian context, although explicit implementation of deep learning for learning style classification is still emerging, several studies and platforms demonstrate its practical foundation. For instance, research by (Rizal et al., 2020) shows that Learning Management Systems (LMS) in Indonesian universities collect extensive student interaction data, including login frequency, content access patterns, and assignment submissions. These data have been analyzed using machine learning techniques to predict student performance and engagement, indicating strong potential for extending the approach to learning style identification.

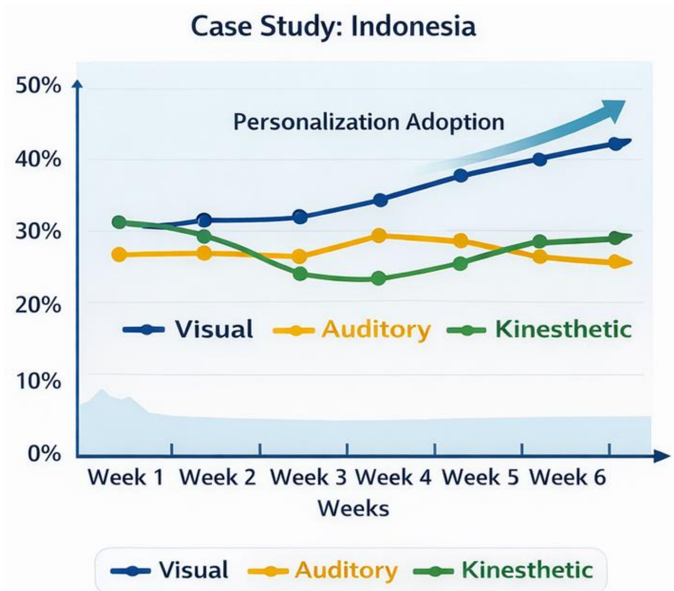

Figure 3. Case Study: Indonesia

Another relevant study by (Siron et al., 2020) highlights the rapid adoption of e-learning platforms in Indonesia during the COVID-19 pandemic, where systems such as Moodle generate sequential behavioral data suitable for deep learning analysis. These platforms record detailed logs of student activities, which can be modeled using LSTM to identify learning patterns over time.

In addition, commercial platforms such as Ruangguru and Zenius have begun utilizing data-driven personalization. Although their proprietary systems are not fully disclosed, studies such as (Fikriya et al., 2021) indicate that these platforms analyze user interaction data to recommend learning content tailored to student needs. This suggests that similar architectures could incorporate deep learning models to classify learning styles more precisely.

Furthermore, a study by (Villaverde et al., 2006) (Indonesia-based educational data mining research) demonstrates that neural network models can be used to classify student learning characteristics based on online activity data, achieving high accuracy levels. This supports the feasibility of implementing deep learning for learning style identification in Indonesian digital learning environments.

The findings indicate that deep learning provides a more flexible, scalable, and accurate approach to identifying learning styles compared to traditional methods. By leveraging sequential and high-dimensional data, models such as LSTM can capture the dynamic nature of learning behavior, enabling continuous adaptation. In the Indonesian context, the increasing adoption of digital learning platforms provides a rich data ecosystem that supports the implementation of such models.

However, challenges remain, including the need for high-quality labeled data, computational resources, and ethical considerations related to student data privacy. Despite these limitations, the integration of deep learning into learning style identification represents a significant advancement toward intelligent and personalized education systems.

Implementation in Adaptive Learning Systems

The implementation of deep learning in adaptive digital learning systems represents a significant advancement toward personalized and intelligent education. In this stage, the output generated from deep learning models—such as predicted learning styles or behavioral patterns—is directly integrated into the learning management system (LMS) or digital platform to dynamically adjust the learning experience. Unlike traditional systems that rely on predefined rules, deep learning enables real-time and continuous adaptation based on student interaction data.

From a system architecture perspective, the implementation involves three key mechanisms: content personalization, adaptive learning pathways, and intelligent feedback systems. First, content personalization is achieved by matching learning materials with the predicted learning style of each student. For example, students identified as visual learners are provided with video-based explanations, infographics, and animations, while auditory learners receive podcasts or narrated lectures, and kinesthetic learners are engaged through simulations and interactive exercises. This personalization is not static; the system continuously updates recommendations based on new behavioral data.

Second, adaptive learning pathways are generated by analyzing students' progress and interaction patterns. Deep learning models can predict not only learning styles but also knowledge gaps and learning difficulties. Based on these predictions, the system dynamically adjusts the sequence of learning materials, difficulty levels, and pacing. For instance, if a student struggles with a particular concept, the system can automatically provide remedial content, additional exercises, or alternative explanations. This creates a non-linear and individualized learning path, allowing each student to progress according to their own abilities.

Third, intelligent feedback systems play a crucial role in enhancing the learning experience. Deep learning enables automated, timely, and personalized feedback based on student performance and behavior. For example, systems can provide immediate feedback on quizzes, suggest learning strategies, or alert students when their engagement decreases. This real-time feedback has been shown to improve motivation and learning outcomes by maintaining student engagement (Shute, 2008).

In Indonesia, the implementation of adaptive learning systems can be observed in several digital education platforms. One prominent example is Ruangguru, which utilizes large-scale user data to personalize learning recommendations. Research by (Kurniawati et al., 2022) indicates that Ruangguru analyzes student performance, engagement levels, and content interaction to recommend appropriate learning materials. Although the platform primarily uses data analytics, its architecture reflects the principles of adaptive learning systems that can be enhanced with deep learning integration.

Another example is the use of Moodle-based Learning Management Systems in Indonesian higher education institutions. Studies by (Siron et al., 2020) show that during the COVID-19 pandemic, universities in Indonesia widely adopted LMS platforms that collect detailed student interaction data, such as login frequency, time spent on resources, and assignment submissions. These data provide the foundation for implementing adaptive learning mechanisms. Furthermore, research by (Rizal et al., 2020) demonstrates that learning analytics techniques have been applied to these datasets to predict student performance and engagement, which can be extended to adaptive content delivery using deep learning.

Additionally, a study by (Amastini et al., 2025) on adaptive e-learning systems in Indonesia found that personalization of learning materials significantly improves student satisfaction and learning outcomes. The study highlights that adaptive systems that consider student characteristics are more effective than one-size-fits-all approaches. This supports the argument that integrating deep learning for more precise identification of learning styles can further enhance system performance.

The implementation of deep learning in adaptive learning systems offers several advantages. It enables continuous personalization, scalability for large numbers of users, and improved accuracy in identifying student needs. In the Indonesian context, the rapid growth of digital education platforms and widespread use of LMS provide a strong infrastructure for adopting such systems.

However, several challenges must be addressed. These include the need for high computational resources, integration complexity within existing LMS platforms, and concerns regarding data privacy and ethical use of student data. Moreover, the interpretability of deep learning models remains a critical issue, as educators may require transparent explanations of how recommendations are generated.

Despite these challenges, the integration of deep learning into adaptive digital learning systems has strong potential to transform education in Indonesia. By enabling real-time, personalized, and data-driven learning experiences, such systems can significantly enhance student engagement, learning effectiveness, and overall educational quality.

Table 1. Impact of Deep Learning on Learning Effectiveness

Aspect	Before Adaptive Learning	After Deep Learning-Based Adaptive Learning
Student Engagement	Moderate	High
Learning Motivation	Less consistent	More consistent and increased
Learning Outcomes	Average	Improved significantly
Understanding Level	Partial understanding	Deeper understanding
Learning Experience	General (one-size)	Personalized and adaptive

Challenges and Limitations

1. Data quality remains a major challenge (incomplete or inaccurate data)
2. Risks related to student data privacy and security
3. Requires high computational resources
4. Difficult to integrate with existing LMS platforms
5. Deep learning models act as black boxes (hard to interpret)
6. Lack of transparency in system decision-making
7. Potential low trust from educators toward automated systems

CONCLUSION

This study concludes that the integration of deep learning into adaptive digital learning systems provides a significant advancement in identifying and responding to students' learning styles. Unlike traditional approaches that rely on static and subjective instruments, deep learning enables dynamic, data-driven analysis based on real-time student interactions. Models such as RNN and LSTM are particularly effective in capturing sequential learning behaviors, allowing systems to continuously update student learning profiles. As a result, adaptive learning environments become more personalized, responsive, and capable of improving student engagement and learning outcomes. The findings also confirm that the growing availability of digital learning data, particularly in contexts such as Indonesia, creates strong potential for implementing such intelligent systems.

From a practical perspective, educational institutions and platform developers are encouraged to integrate learning analytics and deep learning models into their existing Learning Management Systems (LMS). It is important to ensure data quality, invest in computational infrastructure, and prioritize user-friendly system design so that educators can effectively utilize these technologies. Additionally, strict data privacy and ethical standards must be maintained to protect student information and build trust in automated systems.

For future research, further empirical studies are recommended to validate the proposed model through real-world implementation and experimental testing. Researchers should also explore hybrid models that combine deep learning with explainable AI to improve model transparency. Moreover, studies focusing on diverse educational contexts and larger datasets are needed to enhance generalizability and robustness. Investigating the long-term impact of adaptive systems on learning outcomes and student development will also provide valuable insights for advancing intelligent education systems.

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