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Deep Learning Model For Predicting The Risk Of Learning Loss In Primary School Students: Systematic Literature Review

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Abstract :
This research aims to examine the application of deep learning models in predicting the risk of learning loss in elementary school students using a Systematic Literature Review (SLR) approach. With increasing challenges in the world of education, especially due to external factors such as the pandemic and inequality in access to education, artificial intelligence-based methods are needed that are able to accurately identify learning loss risk patterns. This research method is carried out by collecting, analyzing, and synthesizing various studies from leading academic databases to evaluate the effectiveness of deep learning models, such as Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Multi-Layer Perceptron (MLP), in detecting learning loss. The research results show that deep learning models have high potential in predicting learning loss with a good level of accuracy, although there are still challenges in implementation, such as the availability of quality data and model complexity. Therefore, this research highlights the importance of developing a deep learning-based system that is more adaptive and integrated with the educational environment in order to increase the effectiveness of interventions against learning loss in elementary school students.

Keyword *Deep Learning Model, Learning Loss*

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INTRODUCTION

Learning loss is a crucial problem in the world of education, especially for elementary school (SD) students who are at a very important stage of cognitive and social development. Learning loss refers to a decline in academic competence that occurs due to various factors, such as limited access to education, inconsistencies in the learning process, as well as extraordinary events such as the COVID-19 pandemic which causes drastic changes in teaching methods (Engzell et al., 2021). According to various studies, learning loss has a significant impact on students' academic achievement, especially in fundamental subjects such as reading, writing and mathematics. This condition is further exacerbated by social and economic disparities which cause some students to not have equal access to adequate learning facilities. Therefore, an effective method is needed to identify and predict the risk of learning loss to enable appropriate early intervention (Donnelly & Patrinos, 2022).

Along with technological advances in the field of artificial intelligence, deep learning methods have been widely applied in various aspects of data analysis, including in the field of education. Deep learning has the advantage of handling large amounts of data and identifying complex patterns that are difficult to capture by traditional analysis methods. Deep learning models such as Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Multi-Layer Perceptron (MLP) have been used in various studies to analyze students' academic trends and predict factors that influence their achievement. Thus, the application of deep learning models in predicting the risk of learning loss can be an innovative solution in supporting data-based decision making processes in educational environments (Alnasyan, et al., 2024; Munappy, et al., 2022)) .

This research aims to conduct a systematic literature review regarding the application of deep learning models in predicting the risk of learning loss in elementary school students. Specifically, this research focuses on analyzing various deep learning models that have been applied in the field of education, with the aim of identifying the most effective methods in detecting and predicting potential learning loss. By collecting and analyzing various previous studies, this research seeks to provide a comprehensive picture of the development of deep learning technology in supporting education and evaluate the advantages and limitations of the models that have been used.

Apart from that, this research also aims to explore the factors that contribute to learning loss, both from academic and non-academic aspects. Factors such as student attendance, participation in learning activities, socio-economic background, and the effectiveness of teaching methods will be analyzed in the context of how deep learning can be used to understand patterns of learning loss that occur. Thus, it is hoped that the results of this research will provide useful insights for educators, policy makers and educational technology developers in designing learning strategies that are more adaptive and responsive to student needs.

Significance of Research

The significance of this research lies in its contribution in developing artificial intelligence-based approaches to improve educational effectiveness. With the increasing use of technology in the world of education, the use of deep learning in academic analysis can help optimize the learning process and ensure that each student receives attention according to their needs. In addition, the results of this research can also be the basis for developing more accurate and personalized data-based learning systems, thereby helping reduce educational gaps and improving the overall quality of learning.

With this research, it is hoped that various interested parties in the world of education, including schools, government, and technology developers, can understand the potential of using deep learning in overcoming the problem of learning loss. It is hoped that this study will open up opportunities for further research that focuses on the concrete implementation of deep learning models in real educational environments, so that in the end it can produce applicable and sustainable solutions for the education system in the future.

METHOD

This research uses a Systematic Literature Review (SLR) approach to review and analyze relevant studies related to the application of deep learning models in predicting the risk of learning loss in elementary school students. The SLR method was chosen because it provides a systematic and transparent approach in identifying, evaluating and synthesizing the results of previous research (Mohamed Shaffril et al., 2021). The research process began with a literature search from various leading academic databases such as Scopus, IEEE Xplore, SpringerLink, and Google Scholar. Keywords used in the search included "deep learning in education," "learning loss prediction," "neural networks in academic performance," as well as other relevant terms. After that, a selection process was carried out based on inclusion and exclusion criteria to ensure that only relevant and high-quality studies were analyzed further. Inclusion criteria include studies that discuss deep learning models for student academic analysis, while exclusion criteria include studies that are not relevant to the basic education context. Next, a qualitative analysis was carried out on the selected research results to identify trends, advantages and limitations of deep learning models in predicting learning loss. With this approach, the research aims to produce a comprehensive synthesis and provide insight into the development of artificial intelligence-based technology to support learning in elementary schools.

RESULTS AND DISCUSSION

A. Learning Loss Concept

Learning loss is a phenomenon of decreasing students' academic abilities due to disruption in the learning process, both temporary and long term. In the context of basic education, learning loss occurs when students experience difficulty in understanding, remembering, or applying material that has been taught previously (Purwaningsih & Lie, 2024). This phenomenon can be seen from a decline in academic results, low levels of participation in learning, and reduced critical thinking and problem-solving abilities. According to various studies, learning loss often occurs during transition periods, such as long holidays, curriculum changes, or crisis situations that disrupt the continuity of learning. One of the biggest examples of learning loss in recent decades is the impact of the COVID-19 pandemic, which forced schools to implement online learning for a long period of time. Even though educational technology is developing rapidly, not all students have equal access to adequate devices and internet, so many experience delays in understanding the material. In addition, elementary school students who are still in a critical stage of cognitive development are more vulnerable to learning loss than older students, because they rely heavily on direct interactions with teachers and peers to understand new concepts (Kaffenberger, 2021).

There are several main factors that cause learning loss in elementary school students. First, unsupportive learning environment factors, such as lack of access to adequate learning resources at home, lack of guidance from parents, and low socio-economic conditions, which make it difficult for students to develop effective study habits (Zhdanov et al., 2022). The second factor is the quality and continuity of learning. Teachers have an important role in ensuring that material is delivered effectively, but if teaching methods are less varied or do not suit students' learning styles, then understanding of the material will decrease (Alsaleh, 2021). Apart from that, sudden changes in learning methods, such as switching from face-to-face to online, can also hinder the learning process, especially for students who are not yet familiar with technology. The third factor is the psychological aspect and motivation to learn. Boredom, lack of involvement in class, and excessive academic pressure can reduce students' enthusiasm for learning, so they tend to lack focus and have difficulty understanding more complex material (Nappo et al., 2024).

Apart from that, external factors such as health conditions, education policies, and the role of family and society also influence the level of learning loss in elementary school students. Students' physical and mental health plays a major role in learning success, where conditions such as fatigue, malnutrition, or emotional disorders can reduce concentration and memory. Inflexible education policies, such as a curriculum that is too dense or an evaluation system that is less adaptive, can also exacerbate learning loss, especially for students who have limitations in following a fast learning rhythm. The role of family and community cannot be ignored, because parental support in accompanying learning at home and community involvement in providing access to additional learning materials can help reduce the impact of learning loss (Lestari et al., 2024).

Learning loss has a significant impact on students' long-term academic development, especially for those at the primary education level. One of the main impacts is reduced understanding of basic concepts that act as a foundation for learning at the next level. For example, if a student has difficulty understanding basic mathematical operations such as addition and multiplication in the early stages of elementary school, then they will experience obstacles in understanding more complex concepts such as fractions, equations and geometry at a higher level (Page et al., 2021). The same is true for other areas such as literacy, where gaps in reading and writing abilities early on can hinder understanding of more complex texts later in life. This accumulation of learning gaps causes a domino effect which leads to academic performance decreasing as the level of education increases. As a result, many students have difficulty catching up, even after returning to the normal learning system. Without appropriate intervention, learning loss can cause students to lag behind in understanding the material compared to their peers, which ultimately increases the likelihood of them experiencing academic failure or even dropping out of school (Angrist et al., 2021).

Apart from affecting academic understanding, learning loss also impacts students' critical thinking skills and problem-solving abilities in the long term. When students lose the opportunity to practice analytical thinking due to suboptimal learning, they will experience difficulties in developing the ability to analyze information, draw conclusions, and apply concepts in various real-life contexts. For example, in science subjects, if a student does not understand the basic concepts of experimentation or the scientific method at the elementary school level, then they will have difficulty developing investigative skills at the middle school level. Apart from that, collaboration and communication skills that should be acquired through class discussions and group work can also be hampered, especially if learning loss occurs in an online learning context with minimal social interaction. This lack of skills has implications for students' readiness to face academic and professional challenges in the future, because they are not accustomed to the reflective mindset and adaptation skills needed in a dynamic world of work (Kaffenberger, 2021).

The impact of learning loss is not only limited to academic achievement, but can also worsen educational and social inequality in the long term. Students from low economic backgrounds who experience learning loss tend to have limited access to additional educational resources such as private lessons, tutors, or digital-based learning technology. This causes the gap between students who have access to quality education and those who are less fortunate to widen. This inequality has a direct impact on social and economic mobility, where students who experience learning loss have less opportunity to continue their education to a higher level or get a better job in the future. If not addressed immediately, learning loss can become a major factor that prolongs the cycle of poverty, because a lack of academic and professional skills can limit an individual's opportunities to develop and compete in a global world (Blaskó et al., 2022).

B. Deep Learning in Education Analytics

Deep learning is a branch of artificial intelligence (AI) that uses artificial neural networks (ANN) to process large amounts of data and extract complex patterns automatically (Goel et al., 2023). Deep learning models are inspired by how the human brain works in recognizing patterns and making decisions based on experience. In the world of education, deep learning has become a very useful tool for analyzing various aspects of learning, ranging from student academic performance, the effectiveness of teaching methods, to predicting possible learning loss. By using algorithms that are able to carry out learning in stages through layers of neural networks, deep learning can help identify student learning patterns based on historical data, such as test scores, class participation, and interactions on digital learning platforms. This technology allows the education system to become more adaptive and personalized, so that it can provide learning recommendations tailored to individual students' needs and learning styles (Sarker, 2021).

How deep learning works in educational analytics involves processing large amounts of data using various machine learning techniques. Deep learning models are trained on large and diverse datasets, allowing the system to recognize patterns that are invisible to traditional analysis methods (Sridharan et al., 2024). One method that is often used in education is supervised learning, where the model is fed labeled data, such as student test results and attendance rates, to predict future academic performance. Besides that, unsupervised learning It is also often applied to group students based on their learning style or level of understanding of material without requiring labeled data. Another very useful technique in educational analysis is Natural Language Processing (NLP), which is used to understand and analyze texts from students' essays, class discussion forums, as well as their interactions with e-learning platforms. By utilizing this method, educators can gain deeper insight into student learning patterns and the factors that influence their understanding of the material (Pinto & Paquette, 2024).

The implementation of deep learning in education provides many benefits, especially in increasing the effectiveness of learning and assisting in data-based decision making. One of the main applications of deep learning is development adaptive recommendation system, which can adapt learning materials to suit each student's needs (Perrotta & Selwyn, 2020). For example, the system can recommend additional exercises for students who are having difficulty in a particular topic or provide more complex challenges for those with a higher level of understanding. Apart from that, deep learning is also used in predictive analysis, such as detecting the risk of students experiencing learning loss or identifying factors that influence academic success. By analyzing data from various sources, such as test results, interaction patterns in online learning, and in-class activities, deep learning models can provide deeper insight to educators and educational institutions (Sarker, 2021).

Deep learning has become a technology that is widely applied in various fields, including education, to increase the effectiveness of learning and academic management. One of the main applications of deep learning in education is the prediction of student academic performance, which aims to identify factors that influence academic achievement and provide recommendations that can help improve learning outcomes. By using artificial neural networks (ANN), deep learning can analyze large amounts of student data, including test scores, attendance patterns, class engagement, and demographic data, to identify patterns related to academic achievement. The main advantage of deep learning is its ability to automatically recognize patterns in data without requiring excessive human intervention, thereby allowing the system to accurately predict future academic performance. This technology can also be used to identify students at risk of experiencing learning loss, allowing teachers and educational institutions to provide earlier and more targeted interventions (Doleck et al., 2020).

How deep learning works in predicting academic performance involves various machine learning techniques combined with in-depth data analysis. One commonly used approach is supervised learning, where deep learning models are trained using labeled datasets, such as previous exam scores, number of assignments completed, and participation in class discussions. By leveraging this technique, models can learn from historical patterns and use them to predict future test scores or student success in a particular subject (Waheed, et al., 2020). Apart from that, technique unsupervised learning can also be used to group students based on their learning characteristics, such as learning style or level of understanding of concepts. In this way, schools can adapt teaching methods to better suit the needs of individual students. Apart from that, deep learning can also be applied in Natural Language Processing (NLP) to analyze student essays, online forum discussions, and their interactions with digital learning materials, which can provide deeper insight into students' understanding of a topic.

The implementation of deep learning in academic performance prediction has had a major impact on the modern education system. With a predictive system based on deep learning, educators can be more proactive in supporting students' academic development, especially for those who have difficulty understanding subject matter. For example, if the system identifies that a student has a high probability of getting a low score on an upcoming test, the teacher can provide additional guidance or more appropriate learning resources to help the student improve his or her understanding. Apart from that, deep learning can also help in development adaptive learning system, which automatically adjusts the difficulty of the material based on the student's ability, creating a more personalized learning experience (Hernández-Blanco et al., 2019).

C. Relevant Deep Learning Models

1. Convolutional Neural Network (CNN) for visual data analysis, for example handwriting or students' facial expressions.

   Convolutional Neural Network (CNN) is a deep learning architecture that is specifically designed to handle visual data, such as images and videos. CNNs work by extracting features from images through a series of convolutional layers that allow the system to recognize patterns, shapes, and structures in visual data with a high degree of accuracy. This technology has been widely used in various fields, including facial recognition, medical diagnosis, and autonomous vehicles. In the world of education, CNN has great potential for analyzing visual data to improve the quality of learning and understand student behavior in more depth (Wang, et al., 2023). Two examples of major applications of CNNs in educational analytics are the recognition of students' handwriting and the analysis of facial expressions to assess their engagement in learning. By utilizing CNN, educational institutions can develop automatic systems that are able to read, understand, and evaluate visual aspects in the teaching and learning process, which in turn can help teachers provide more effective interventions.

One of the main applications of CNN in educational analytics is the recognition of student handwriting, which is very useful in digital-based learning systems. CNN models can be trained to recognize handwritten characters from various individuals, including different writing styles, stroke thicknesses, as well as variations in letter shape. By applying this technology, learning systems can convert students' handwriting into digital text, which not only facilitates automatic correction but also allows academic data to be stored in a more structured manner. Additionally, handwriting recognition with CNN can be used to detect errors in writing numbers or letters on math and language tests, helping students develop their writing skills more effectively (Khan et al., 2020). This technology can also be applied in handwriting analysis to assess the speed and quality of students' writing, so that teachers can identify students who experience motor difficulties or obstacles in writing. Thus, the application of CNN in handwriting recognition not only increases the efficiency of academic evaluation, but also helps in personalizing learning that is more responsive to student needs.

Apart from handwriting recognition, CNN can also be applied in the analysis of students' facial expressions to assess their engagement and emotions during the learning process. By using a dataset containing various facial expressions, a CNN can be trained to identify students' emotions, such as confusion, interest, or boredom, based on their facial expressions while in class or while participating in online learning. This analysis is very useful for educators to understand the level of student engagement in real-time and adjust teaching strategies to be more effective (Alzubaidi et al., 2021). For example, if the system detects that the majority of students show expressions of confusion during the explanation of a concept, the teacher can immediately adjust the teaching approach or provide additional examples to make the material easier to understand. In online learning environments, this technology can also be used to measure student participation levels, provide teachers with insight into how well students are paying attention to the material, and help identify those who need additional help.

The application of CNNs in visual data analysis in education brings many benefits, from automating academic evaluations to monitoring student engagement more accurately. However, there are several challenges that need to be overcome in its implementation, such as the need for large, high-quality datasets, as well as concerns regarding the privacy and security of student data (Lopez Pinaya et al., 2020). To ensure ethical use of this technology, there needs to be a clear policy regarding the collection and use of student visual data, including privacy protection measures and consent from relevant parties. In addition, the development of lighter and more efficient CNN models is needed so that this technology can be widely applied in educational environments with limited computing resources.

2. Recurrent Neural Network (RNN) or Long Short-Term Memory (LSTM) for analysis of sequential data such as grade history and learning interactions.

   In the world of artificial intelligence, Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) are two types of deep learning architecture designed to handle sequential data, such as text, voice and time-based data. In contrast to conventional neural networks that treat each data independently, RNNs and LSTMs are able to retain information from previous inputs to understand relationships in data sequences (Sherstinsky, 2020). This capability makes RNN and LSTM very useful in educational data analysis, especially in predicting students' academic performance based on their grade history and interaction patterns in learning. By utilizing this model, educational institutions can gain deeper insight into student development over time and design more adaptive learning strategies. One example of its application is in learning recommendation systems, where models can analyze students' learning patterns and provide recommendations for the most appropriate materials or teaching methods based on their individual needs.

One of the main advantages of RNN and LSTM in education is their ability to process sequential academic data, such as historical test scores, attendance patterns, and the development of student skills over time. By using this model, the system can identify patterns that show trends of increasing or decreasing academic performance and anticipate potential learning loss. For example, if a student experiences consecutive drops in grades in several subjects, the LSTM model can identify this pattern and provide a warning to the teacher or school to intervene immediately. Apart from that, sequential data analysis can also be used to understand the impact of teaching strategies on student learning outcomes. By tracking the pattern of changes in grades after implementing a particular learning method, schools can assess the effectiveness of the approach and adjust it to improve overall academic results.

Apart from value analysis, RNN and LSTM can also be applied in studying student interactions with online learning platforms. With the increasing use of digital technology in education, student interaction data in Learning Management Systems (LMS) systems or AI-based learning applications can be used to evaluate the engagement and effectiveness of learning methods. RNN or LSTM models can analyze students' access patterns to course material, time spent reading or doing assignments, and participation levels in online discussions to understand how they absorb information. If the model detects that a student rarely interacts with the material or is having difficulty consistently completing assignments, the system can make suggestions to educators to provide additional support, such as more tutoring or material that better suits the student's learning style. Thus, this technology not only helps improve the efficiency of academic evaluation, but also creates a more personalized and adaptive learning experience (Kaur & Mohta, 2019).

The application of RNNs and LSTMs in educational data analysis offers many benefits, but also faces several challenges that need to be overcome. One of the main challenges is the need for large amounts of high-quality data to train models effectively. Additionally, because these models rely on historical data, it is important to ensure that the data used is relevant and does not contain biases that could affect predictions. Aspects of data privacy and security are also major concerns in implementing this technology, considering that student academic data is sensitive. Therefore, schools and educational institutions must ensure that the implementation of RNN and LSTM is carried out taking into account ethics and strict data protection policies (Khan, S. 2024).

3. Multi-Layer Perceptron (MLP) for numerical feature-based classification such as grades, attendance, and student participation.

   Multi-Layer Perceptron (MLP) is a type of artificial neural network (ANN) that is widely used in various classification and regression tasks, especially in numerical feature-based data analysis. MLP consists of several layers of neurons, including input layers, hidden layers, and output layers, which allows this model to learn complex relationships between input and output variables. In an educational context, MLP can be used to classify students based on various numerical features such as academic grades, attendance, and participation in learning activities. By utilizing this model, schools and educational institutions can develop prediction systems that are able to identify students at low or high risk in academic achievement, thereby allowing for faster and more targeted interventions.

One of the main applications of MLP in the world of education is the classification of students' academic performance based on their grade history. These models can be trained using datasets containing test scores, assignments, and projects, as well as other factors such as the number of hours studied or involvement in class discussions. By applying backpropagation algorithms and nonlinear activation functions such as ReLU or sigmoid, MLP can identify patterns in data that indicate trends in academic success or failure. For example, the model can classify students into categories, such as “high achievers,” “average,” or “at risk of failure,” based on their grade patterns. This information can be used by teachers and schools to provide additional support to students who are experiencing difficulties, for example through tutoring or adjusting teaching strategies. Thus, the application of MLP in numerical feature-based classification can help increase the effectiveness of academic evaluation and support more personalized learning (Yılmaz et al., 2022).

Apart from academic grades, student attendance and participation are also important factors in determining learning success. By using MLP, schools can develop a classification system that analyzes student attendance data and their level of participation in class, both in face-to-face and online learning. This model can identify patterns that show a relationship between students' frequency of attendance and engagement and their academic performance. For example, if the model finds that students with low attendance tend to have lower grades, schools can take preventative steps such as providing early warnings or academic counseling to students who are frequently absent. In addition, in online learning, MLP can be used to analyze student activity logs, such as the amount of time spent accessing material, the level of interaction in online discussions, and assignment completion. By understanding these patterns, educational institutions can develop more effective learning strategies and ensure that each student gets the support they need to achieve academic success (Turkoglu & Kaya, 2020).

Although MLP offers many benefits in numerical feature-based classification in the educational field, there are several challenges that need to be considered in its implementation. One of the main challenges is the need for high-quality data and large enough quantities to train models with good accuracy. Incomplete or biased data can reduce a model's effectiveness in making accurate predictions. Therefore, it is important for schools to manage and clean data before using it in an MLP-based system. In addition, model interpretability is also a challenge, because artificial neural networks are often considered a "black box" that is difficult to explain. To overcome this, methods such as explainable AI (XAI) can be used to provide more transparent insight into how the model makes decisions (Heidari et al., 2020).

CONCLUSION

This research reveals that the application of deep learning models in predicting the risk of learning loss in elementary school students has great potential in increasing the effectiveness of data-based education. With deep learning's ability to process and analyze academic data in depth, this model is able to identify patterns that contribute to learning loss, thereby enabling earlier and more targeted intervention. Results from a systematic literature review show that various deep learning models such as Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Multi-Layer Perceptron (MLP) have been widely used in academic analysis and show high prediction accuracy. However, there are challenges in its implementation, such as the need for large, high-quality data and complexity in interpreting model results. Therefore, the development of deep learning systems in education must be supported by adequate infrastructure and collaboration between educators, researchers and technology developers. With the right approach, the application of deep learning can not only help minimize the risk of learning loss but also contribute to improving a more personalized and adaptive learning experience for elementary school students.

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