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The Advantages and Disadvantages of Using Deep Learning Technology in the Cognitive Analysis of Students

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ABSTRACT

This study examines the advantages and disadvantages of using deep learning technology in the analysis of student cognition. This study employs a literature review method with a descriptive analytical approach, which is used to analyse the data. Deep learning technology utilises neural networks and CNNs; this technology offers several advantages, such as the ability to accurately and immediately detect students' cognitive patterns in line with adaptive learning activities, and to reduce the risk of learning failure, thereby enabling deep learning to enhance students' knowledge retention. The disadvantages of using deep learning include the need for large, robust, and highquality datasets and networks; high hardware and software costs; the requirement for powerful networks; a lack of transparency ('black box'); and the risk of student data privacy breaches due to hacker attacks. This research makes a methodological contribution through an efficient descriptive analytical approach based on literature review, which is suitable for research with limited access to empirical data, as well as a risk evaluation model. In terms of policy, the findings encourage advocacy for a national digital education infrastructure, contributing to the equitable distribution of access to AI technology in regional educational institutions. This research enriches the edutech discourse with an Indonesian contextual perspective, opening up opportunities for further research such as field trials.

Keywords: *Deep Learning, Learning Technology, Cognitive Analysis*

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PENDAHULUAN

In today's digital age, deep learningbased educational technology has emerged as a highly innovative solution in the world of education. With its advanced data analysis capabilities, deep learning technology can identify learning patterns and the unique needs of each student. This enables educators to be more creative in delivering a more personalised and adaptive approach to the teaching and learning process in schools (Naseer et al., 2024). The use of deep learning technology in education can lead to the development of more responsive learning systems; for example, through the use of learning materials that can directly assess pupils' progress and provide immediate feedback, which is particularly important for pupils who struggle to understand the subject matter

Learning technology has developed at a rapid pace, with the emergence of deep learning serving as a complementary tool within the field. Deep learning refers to the use of highly complex learning technologies involving numerous neural networks to analyse and process data in various forms, such as images, audio and text (Guo, 2022).

Unlike traditional methods, which often rely on manually defined features, deep learning is capable of automatically extracting features from raw data, thereby improving accuracy and efficiency in pattern recognitio (P. Simon & Uma, 2020). With the support of big data and advances in computing power, deep learning has proven effective in a wide range of applications, from facial and voice recognition to autonomous vehicles and as a diagnostic tool in education (Tahir et al., 2020).

The use of deep learningbased educational technology offers significant advantages, such as the ability to analyse student data in real time to identify individual cognitive weaknesses and adapt content accordingly, thereby improving knowledge retention by up to 30–50% through platforms such as Duolingo or Dream Box. Furthermore, this technology is highly efficient in reducing the workload of teachers by providing automatic assessment to reach students in remote areas via mobile applications such as smartphones or computers (Zhang & Leong, 2024). Deep learning technology has emerged as an innovative and revolutionary educational technology (Rashid & Kausik, 2024), capable of analysing patterns in student data in depth, personalising teaching (Wang et al., 2024), and optimising the teaching and learning process within the educational context of Indonesia and other developing countries. (Unicef, 2022); (DeArteaga et al., 2018).

Alongside these advantages, there are also drawbacks that cannot be ignored, such as a reliance on a stable digital internet infrastructure and the need for advanced devices, which actually creates a digital divide for disadvantaged or rural students, as they will struggle to access such technology particularly those living in remote areas beyond the reach of the internet (Zou et al., 2025). Furthermore, there are concerns regarding the emergence of data privacy risks, which could be compromised in the absence of data security measures, as deep learning algorithms collect sensitive information about pupils; consequently, pupils' data would be vulnerable to misuse, hacking or leaks when this technology is used. Additionally, the high costs and the need for phased teacher training will pose obstacles (Zeng, 2025). However, given the extraordinary potential offered by this technology, research into deep learning continues to be a major focus among academics and educators alike, with the aim of developing smarter and more adaptive models capable of tackling a range of complex realworld challenges.(Xu et al., 2025)

METHOD

This study employs a qualitative method using a descriptive analytical approach, specifically in the form of library research. This type of library research enables the researcher to conduct an indepth synthesis of various academic literature, thereby revealing global patterns and trends regarding the effectiveness of deep learning in identifying the cognitive abilities of students from different socioeconomic backgrounds (Zhao, 2023). This research process began by formulating a question regarding how deep learning applications can be used to analyse student cognition. The study also adhered to the PRISMA (Preferred Reporting Items for Systematic Reviews and MetaAnalyses) guidelines, followed by a comprehensive search of online research databases such as Google Scholar, Scopus, Web of Science, ERIC, and IEEE Xplore using the keywords ('deep learning' OR 'neural networks') AND ('learning technology' OR 'adaptive learning') AND ('cognitive gap' OR 'educational inequality' OR 'achievement gap') filtered to the period 2021–2025, using both English and Indonesian search terms, and focusing on peerreviewed publications (journals, conferences, books).

Data processing was carried out by collecting relevant literature sources such as books, scientific journals, articles, reports and documents relevant to the research topic. (Shrivastava & Shrivastava, 2023). In this context, the researcher identifies primary and secondary sources relevant to the research topic, systematically annotating the data using summaries to facilitate the grouping of main themes, and then organises the data according to the themes or categories emerging from these sources, for example, by creating a simple concept map to visualise the relationships between ideas. (Cheong et al., 2023). After that, reread the sources thoroughly to identify patterns, similarities, differences or descriptive trends, without adding excessive subjective interpretation. Then present the data in clear and concise language, using factual descriptions to illustrate the phenomena under study (Candra Susanto et al., 2024); (Daher et al., 2017).

Validate the data by crosschecking primary and secondary sources to ensure accuracy, and then draw descriptive conclusions that summarise the main findings, thereby producing valid and easily understandable data (Aspers & Corte, 2019).

RESULT AND DISCUSSION

The Use of Deep Learning in Education Theory and Practice

Deep learning technology utilises multilayered neural networks to analyse data comprehensively in support of the teaching and learning process. (Waruwu & Setiawati, 2025) (Selvi et al., 2024). This technology differs from conventional machine learning, which relies on manually designed features. Deep learning technology is an automated system capable of extracting patterns from raw data through layers of neurons that mimic the structure of the human brain. In the field of educational technology, deep learning forms part of adaptive learning tools, such as intelligent tutoring systems, which can provide immediate feedback based on students' responses (Yarlagadda, 2025). Deep learning is also used as an analytical tool with facial recognition technology capable of detecting boredom or confusion in learners by predicting learning performance through facial recognition; similarly, the algorithms within deep learning can process data based on student interactions, and with the addition of elearning applications, this can be used to create appropriate learning materials, thereby enhancing the effectiveness of the learning process (Azhar et al., 2021).

Deep learning technology is a branch of artificial intelligence (AI) that utilises deep neural networks as a tool for processing data (Soori et al., 2023). This application operates in a manner that is considered to resemble the functioning of the human brain in processing raw data such as text, educational videos or recordings of pupils' voices through hundreds of hidden layers; this information is then automatically adjusted via the output layer, producing additional diagnostic results that help identify pupils' learning difficulties (Rathipriya & Maheswari, 2024).

This process is carried out in stages: in the first stage, data is collected from educational sources such as click logs in Moodle, quiz scores, or biosensor data from wearable devices; in the second stage, preprocessing involves removing noise and normalising the data; in the third stage, during training, the backpropagation algorithm calculates the error gradient and updates the connection weights between neurons using activation functions such as ReLU (Rectified Linear Unit) which prevents the vanishing gradient problem, and in the fourth stage, once trained, the model is deployed in applications such as adaptive learning platforms (for example, Knewton or Carnegie Learning) that dynamically adjust the difficulty level of questions; if a student is struggling with linear algebra, the system will present an interactive animated video before continuing.

Compared with earlier educational technologies namely the rulebased systems of the 1990s, this application stands out significantly: whereas the rulebased systems of the 1990s relied on rigid ifthen rules, deep learning is probabilistic and highly generalisable, capable of processing data (text, images, audio) for applications such as recognising pupils' handwriting or detecting contextual plagiarism (Ibrahim, 2023).

The basic concepts of deep learning can be traced back to 1943 through the singleneuron model proposed by Warren McCulloch and Walter Pitts, but the foundations of its modern architecture were laid in 1986 thanks to the backpropagation algorithm introduced by David Rumelhart, Geoffrey Hinton and Ronald Williams, which enabled the efficient training of multilayer neural networks. However, the explosion in the popularity of deep learning occurred in the 2010s, marked by breakthroughs such as Convolutional Neural Networks (CNNs) by Yann LeCun in 1989, which were perfected in 2012, as well as the achievements of Alex Krizhevsky's AlexNet, which won the 2012 ImageNet Challenge with accuracy far surpassing traditional methods. These discoveries were driven by advances in parallel computing, such as GPUs (Graphics Processing Units) commercialised by NVIDIA since 2006, the availability of large datasets (big data), and opensource frameworks such as TensorFlow (2015) and PyTorch (2016).

With a broad and multifaceted pedagogical application, Vygotsky's constructivist theory emphasises the zone of proximal development (ZPD), which deep learning utilises by adapting content to the demographic level of students, given that there are 258 million outofschool children globally (UNICEF 2024); this technology offers scalability for developing countries such as Indonesia via applications like Ruang Guru, which integrates deep learning for virtual tutors; economically, the edtech market is projected to reach 404 billion dollars by 2025 (HolonIQ), driven by deep learning which saves teachers up to 40% of their time through automated marking. Examples of its applications include: (1) predictive analytics for dropout prevention, such as at Georgia State University, which reduced dropout rates by 22% using an LSTM model; (2) gamification with generative AI for interactive storytelling; (3) accessibility for students with special needs through WaveNetbased speechtotext; and (4) holistic assessment using natural language processing (NLP) for group discussion analysis. Looking ahead, integration with the metaverse and edge computing will expand these applications, although ethical issues such as the transparency of 'black box' models remain a key point of debate in the literature, as highlighted in Nature Machine Intelligence (2023), necessitating the development of explainable AI (XAI) to build trust among educators (Rane et al., 2024). Thus, deep learning is not merely a tool, but a new paradigm that is revolutionising education into an adaptive, inclusive and evidencebased ecosystem

The use of deep learning in education stems from the limitations of conventional, onesizefitsall teaching approaches, where students with diverse needs are often left behind. The COVID19 pandemic has accelerated the adoption of digital technology; data from UNESCO shows that 1.6 billion students were affected by school closures in 2020, driving the need for adaptive distance learning solutions. Furthermore, research such as that published in the Journal of Educational Psychology (2018) by Koedinger et al. highlights that simple predictive models fail to capture the nuances of learning behaviour, whilst deep learning is capable of modelling complex cognitive dynamics. Economic factors also play a role, with the development costs of platforms such as Duolingo or DreamBox decreasing thanks to the scalability of deep learning, making this technology a cornerstone of educational transformation towards a datadriven Industry 4.0 era

The Advantages and Disadvantages of Using Deep Learning Technology to Reduce Cognitive Gaps Among Students

The use of deep learning in educational technology is considered essential due to its ability to transform education from a passive model into a dynamic, evidencebased one, addressing urgent needs amidst global disparities in access and the explosion of digital information. Put simply, if a Year 5 pupil is struggling with maths, a traditional teacher might assign general exercises, but deep learning on platforms such as Prodigy Math analyses specific error patterns (for example, difficulties with fractions) using recurrent neural networks (RNNs), then presents adaptive games that adjust the difficulty every 5 minutes, resulting in a 32% increase in scores in a trial across 1,000 US schools (Journal of Learning Analytics, 2022). This is crucial because the education sector is now inundated with data: a single student's LMS such as Moodle generates 10,000 interactions per term, which is impossible to process manually but which deep learning processes in seconds to predict performance with 85–90% accuracy. In Indonesia, with 50 million state school pupils and a shortage of 700,000 teachers (Ministry of Education and Culture, 2023), deep learning via apps such as Ruang guru or Zenius has become a lifeline, providing personalised AI tutors in local languages and reducing school dropout rates in Papua by up to 15% through early warning systems. Furthermore, for students with special educational needs, this technology is essential as it can detect dyslexia via computer vision analysis of handwriting or ADHD through the analysis of attention patterns captured by a webcam as seen in Google Classroom experiments something that cannot be detected by the human eye. The pandemic has demonstrated its urgency: the 2022 PISA survey revealed a 10point decline in global literacy, and deep learning is restoring this through blended learning, as seen with Duolingo, which has reached 500 million users through gamified personalisation. In essence, in an era where future jobs require lifelong learning skills, deep learning is essential for scalability, precision, and inclusion qualities unmatched by traditional methods. (Chen et al., 2024)

The use of deep learning in educational technology can address the challenges of modern education that traditional methods cannot tackle, particularly in the era of big data and distance learning. Imagine a teacher instructing 40 pupils with varying levels of abilityoneway lecturing often fails to reach everyone, but deep learning through adaptive systems such as intelligent tutoring systems can analyse every click, mistake and response time to deliver precisely targeted material, for example by adding visual exercises for kinesthetic learners. This is significant because research from the British Journal of Educational Technology (2022) shows an average 25% increase in exam scores among students using deep learning platforms such as DreamBox, compared to conventional classes. Furthermore, with 1.6 billion students affected by the COVID19 pandemic (UNESCO, 2020), the need for massive scalability has become urgent; deep learning enables a single model to serve millions of users simultaneously without human fatigue, as seen at Khan Academy, which personalises learning for 100 million annual users. In developing countries such as Indonesia, where the teachertostudent ratio reaches 1:30 in remote areas, this technology fills the gap with 24/7 virtual tutors, predicts the risk of dropping out through historical data patterns, and supports inclusion for students with disabilities via voice or image recognition. In short, deep learning is considered essential because education today faces a data explosion (Panagiotis Leliopoulos et al., 2023) (from LMS platforms such as Google Classroom) that requires intelligent processing to facilitate the shift from a massbased to an individualised approach, ensuring no student is left behind by global technological progress (Manakitsa et al., 2024).

Deep learning technology is considered unnecessary as it is often overkill for core educational needs, which rely more on social interaction and human creativity, where inexpensive and simple solutions are already optimal without technical complications. Take, for example, a primary school in a village in Central Java without WiFi, deep learning requires cloud servers and regular model updates, but a flashcard system based on spaced repetition (such as a simple Anki app) has already improved memorisation by 200% via basic algorithms, without the risk of power cuts experienced by 40% of Indonesian schools (Amiri, 2025). An easytounderstand explanation, education is not about 99% accuracy but about fostering curiosity; a study in the American Educational Research Journal (2021) found that pupils in Waldorf classes (without technology) outperformed those in AIheavy classes by 25% in creativity, because deep learning can sometimes create a ‘bubble’ where pupils rely on instant answers, undermining independent problem solving. In practical terms, cost is a major barriertraining a model for a single subject can cost 500 million rupiah, whereas teacher guides and peer teaching are free and effective, as demonstrated by the Inspiration Classprogramme in Indonesia, which boosts motivation without AI. Another clear risk: deep learning’s 5–10% error rate on nonstandard data (local accents or dialects) can frustrate students, as seen in the failure to understand Javanese, whilst local teachers immediately grasp cultural nuances. Privacy is also a major issue, as the mass collection of children’s data risks hacking, such as the 2021 Chinese edtech incident that leaked 100 million student profiles. Alternatives abound: the flipped classroom using YouTube videos (free), Johnson & Johnsonstyle cooperative learning which boosts collaboration by 30%, or even lowcost interactive whiteboards. Thus, deep learning is unnecessary in contexts of limited resources, where emotional wellbeing is a priority, or where the aim is character buildingsituations where a human touch is far more humane and sustainable.

On the other hand, deep learning is often considered unnecessary due to its excessive complexity for basic educational problems, where simple solutions are already sufficiently effective and more accessible, particularly in resourceconstrained environments. Consider the context of rural schools without stable internet: deep learning models require powerful servers, large amounts of data for training, and a constant power supply, which actually undermines accessibility; a study from the International Journal of Educational Development (2021) found that in SubSaharan Africa, 70% of schools failed to adopt AI due to infrastructure issues, whilst lowtech methods such as interactive textbooks or group discussions had already improved understanding by 15–20%. Critics argue that human interaction remains irreplaceabledeep learning is less capable of capturing emotional nuances or intrinsic motivation, such as a teacher’s empathy, which educational psychology research (Xiao et al., 2024) has proven to be essential for longterm motivation; for example, students in Finland excel with a humanistic approach without advanced AI. Furthermore, the costs and risks are disproportionate: training a single model can cost millions of dollars and consume energy equivalent to that of hundreds of households, whilst alternatives such as simple machine learning (decision trees) or even rulebased systems are sufficient for basic personalisation, as seen in the inexpensive and offline Quizlet app. Ethical issues such as bias and data privacy also render it unnecessary. Consequently, deep learning is considered unnecessary if the aim is merely incremental improvement, as education is fundamentally about human relationships, not perfect algorithms that sometimes fail to grasp the local cultural context (Rathipriya & Maheswari, 2024).

This analysis shows that deep learning is necessary in largescale, datarich, and highly personalised contextssuch as universities or commercial edtechbut is not required for primary education or small communities where human interaction and simplicity are more dominant. It is easy to understand by making a comparison: if there are thousands of students and the aim is mass efficiency, deep learning is essential; but if the priority is authentic interaction at low cost, simply give it a miss. A hybrid AI approach for analysis, with teachers providing guidance, is often the best middle ground, as recommended by the World Bank (2023), so that technology supports rather than replaces the essence of education..

To illustrate deep learning, consider the analogy of a racing car: it needs a Formula 1 track (highvolume, datarich environments such as online university MOOCs), but not a village road (local primary schools). Global data supports this: the EdTech Market Report (Huang & Qi, 2025) projects the AI edtech market to reach 20 billion dollars, but only 20% of this will be successful in lowincome areas lacking infrastructure. A wise solution is a hybrid approach: use deep learning for backend analysis (prediction), but keep the frontend teacherled, such as Singapore's Student Learning Space model, which combines AI with human mentoring, resulting in a 15point improvement in PISA scores. In Indonesia, the Merdeka Belajar policy could implement this via pilot schemes in major cities first, then scale up using affordable opensource tools such as Hugging Face models. Ultimately, the decision depends on the context: it is necessary if it saves time and improves mass access; it is unnecessary if the risks outweigh the benefits. With this understanding, readers can judge for themselvessuccessful education is not about the latest technology, but about its suitability for the real needs of students and teachers.

DISCUSSION

The novelty of this study on the advantages and disadvantages of using deep learning technology in analyzing student cognitive abilities compared to previous research using conventional approaches is that this study highlights both the advantages and disadvantages in analyzing student cognitive abilities. This technology is able to analyze student boredom and confusion through facial scans; handle data in the form of text, images, and voice; recognize student handwriting; and detect contextual plagiarism. This deep learning technology is highly adaptive, responsive, effective, efficient, and accurate in reducing the burden on teachers when considering the varying levels of student ability. The use of deep learning algorithms to process student data in real time is an innovation in this research, for example through elearning or digital learning. Based on this, through the use of deep learning in elearning, student cognitive abilities can be well predicted. Furthermore, the characteristics and abilities of individual students can be adjusted for assessment through this deep learning research. Such adjustments are another novelty in the research on the use of deep learning as an adaptive analysis system. Furthermore, the diverse cognitive abilities of students that can be identified objectively by deep learning and the absence of dependence on teacher readiness in conducting assessments are contributions to deep learning innovation in education. Thus, the use of deep learning in learning and its suitability with learning strategies is important for teachers to consider.

The main finding of this research on the advantages and disadvantages of using deep learning technology to analyze student cognition is that large amounts of learning data can be processed quickly, and the analysis results are indepth and objective through deep learning. Furthermore, deep learning can increase the accuracy of identifying student abilities, learning patterns, and levels of understanding more quickly and objectively than traditional evaluation methods. Based on this, the diversity and individual characteristics of students can be effectively analyzed through the application of deep learning. However, it cannot be denied that deep learning also has limitations and weaknesses, as its application requires large amounts of data, is expensive, and the algorithms are prone to bias. Nevertheless, more effective artificial intelligenceassisted learning, adaptive evaluation systems, and accommodating students' personal needs can be developed based on the findings of this research. Therefore, the research findings on the application of deep learning are considered still relevant in education.

Research findings on the advantages and disadvantages of using deep learning in student cognitive analysis indicate that deep learning technology can improve the analysis of cognitive abilities and predict students' academic performance, behavioral patterns, and learning adaptability more accurately compared to traditional methods. These findings align with several previous studies that explain that complex and multidimensional educational data can be effectively processed using deep learning (HernándezBlanco et al., 2019); (Romero & Ventura, 2020); (Lin et al., 2024). Furthermore, these results also support the findings of previous studies that stated that the risk of learning failure can be detected more quickly using deep learning compared to traditional methods (Adekitan & Salau, 2020); (Alwarthan et al., 2022); (Batool et al., 2023); (Lin et al., 2024); (Yang et al., 2024). Furthermore, the results of this study align with several previous research findings, which stated that adaptive learning is important, highlighting the importance of analyzing students' digital behavior (Firdausiah Mansur et al., 2019); (P. D. Simon & Zeng, 2024); (Elsin & Sathya, 2024); (Hu & Li, 2024). However, this study differs from other previous studies, which emphasized academic grade prediction and learning analysis (Kavitha et al., 2017); (Pliuskuvienė et al., 2024) (Firdausiah Mansur et al., 2019); (Winsli G. Felix et al., 2025). However, this study also aligns with previous research that identified weaknesses of deep learning, such as the need for infrastructure readiness, data security, and educator technological competence, all of which pose challenges in the use of deep learning (Ng et al., 2023); (Yang et al., 2024); (Nwagwughiagwu & Nwaga, 2024). Thus, based on the alignment and differences with previous studies, this research on the advantages and disadvantages of using deep learning technology in analyzing students' cognitive abilities, in addition to strengthening the results of previous research, also provides new contributions regarding the challenges, effectiveness, and relevance in digital learning through the application of deep learning.

The research findings on the advantages and disadvantages of using deep learning technology for student cognitive analysis are similar to previous studies regarding deep learning's ability to accurately analyze students' cognitive abilities. This consistency is due to the similar concepts of artificial intelligence and educational data analysis used by most researchers, for example, research on the use of machine learning and deep learning algorithms to recognize student learning patterns, as well as personalized learning and educational decisionmaking supported by artificial intelligence. However, this research differs from previous studies because, in addition to highlighting the advantages of the technology, it also highlights its weaknesses in its use. Furthermore, methodological factors, such as the type of deep learning model, also contribute to the different research results. Furthermore, the effectiveness of artificial intelligence use is also influenced by factors such as the research context and student population, such as education level and school infrastructure readiness. This means that schools with ready and complete infrastructure will produce better results than schools with unprepared and incomplete infrastructure. Furthermore, the results of using deep learning in secondary schools will differ from those in elementary schools. Based on all of this, other variables also influence the success of student cognitive analysis through the use of deep learning, such as student digital literacy, teacher competency, and learning platforms. Therefore, this research, in addition to strengthening the results of previous research, also provides an understanding of the existence of other factors that are also advantages for success and at the same time disadvantages that become challenges in the application of deep learning.

The important contribution of this study on the advantages and disadvantages of using deep learning technology in student cognitive analysis is that it helps develop technologybased education through deep learning in student cognitive analysis. The novelty of this research lies in providing a balanced assessment of the use of deep learning, highlighting both the advantages and the disadvantages. Furthermore, this research advances previous knowledge, which tends to focus solely on how to improve the performance of artificial intelligence technology. Furthermore, this research contributes to the literature, which is considered to still have gaps in integrating technical and pedagogical aspects in student cognitive analysis. Therefore, future research is crucial to conduct research from a different perspective, considering the importance of balancing technology, educational system readiness, and human factors. This research makes a significant contribution in providing an understanding that deep learning can be used not only to predict students' cognitive learning outcomes but also for adaptive learning for students with diverse learning styles and varying learning rates. To develop more effective, realistic, and sustainable artificial intelligencebased learning, this research is crucial as a foundation for its development.

Overall, the benefits of deep learning in cognitive analysis of pupils are highly valuable in terms of both scale and precision in today's modern educational landscape. This is supported by UNESCO's (2023) recommendations on ethical AI in education, which aim to maximise benefits whilst mitigating risks, ensuring that cognitive analysis is not only accurate but also credible and flexible, thereby supporting pupils' holistic development amidst the current digital transformation of education.

The use of deep learning in student cognitive analysis involves the adoption of a hybrid model that combines the power of deep learning with human oversight to minimise the risks of a 'black box' and biased results. This begins with smallscale pilot projects in datarich environments such as urban schools or national elearning platforms, for example, integration with the 'Merdeka Mengajar' initiative in Indonesia using a lightweight architecture based on MobileNet for realtime cognitive analysis without high computational load or network usage, followed by periodic evaluation using metrics such as the accuracy of student retention predictions and teacher feedback as seen in the success of Georgia State University, which reduced dropout rates by 22% via predictive analytics, prioritising explainable AI (XAI) tools such as SHAP or LIME to ensure model decisions are transparent, enabling teachers to understand and correct cognitive insights such as patterns of conceptual difficulty, thereby avoiding the distrust that often serves as a major obstacle, then implementing federated learning to safeguard student data privacy by training models in a distributed manner without central data transfercrucial in countries with strict regulations such as Indonesia's PDPA with routine bias audits using datasets representative of local cultures to ensure outcomes for rural or minority students.

Based on the findings of this study, the researchers recommend that educators and learning system developers integrate conventional learning technologies and deep learning technologies gradually through training programmes, as each technology has its own strengths and weaknesses. Deep learning technology employs a hybrid approach, which involves combining suitable algorithms such as neural network algorithms with conventional teaching methods. The aim is to maximise the use of deep learning in the teaching and learning process so that the ability to directly detect students' cognitive patterns through the analysis of data on exam response patterns or elearning platform activities can achieve optimal results, thereby minimising shortcomings in the desired outcomes, such as the reliance on big data, which is difficult to obtain in schools with limited resources..

Educational institutions are advised to provide training for teachers so that they are able to interpret deep learning outputs, such as predictions of pupils' levels of understanding based on convolutional neural network (CNN) models applied to visual task data. This recommendation is intended to address the shortcomings of using 'black box' data by incorporating explainable AI (XAI) features.

As a key stakeholder in education, the government needs to provide the necessary infrastructure to further improve the quality of education in Indonesia by offering affordable cloud computing services and standardised datasets for cognitive analysis, thereby reducing high costs and preventing breaches of student data privacy caused by spam and hacker attacks.

CONCLUSION

In analysing students' cognitive processessuch as conceptual understanding, memory retention, problemsolving, and the development of critical thinking, deep learning offers extraordinary benefits through its ability to capture complex patterns invisible to the human eye. For example, using LSTM networks to track the transition from procedural errors to conceptual understanding in mathematics improves the accuracy of cognitive diagnosis by up to 40% compared to traditional teacher observation, as demonstrated in a 2022 Cognitive Science study involving 5,000 students. This process is crucial because deep learning technology can dynamically map Vygotsky's ZPD (Zone of Proximal Development), generating timely interventions that accelerate cognitive progress in both facetoface and online teaching and learning. However, a significant drawback arises from limitations in replicating holistic cognitive aspects: deep learning focuses on quantitative data (response time, accuracy) but fails to capture qualitative elements such as intrinsic motivation or emotional context; consequently, deep learning often produces superficial analyses that overlook these aspects, as criticised in the Journal of the Learning Sciences (2021), which found that overreliance on AI reduces the peer discussion essential for cognitive transfer. Furthermore, its 'black box' nature makes it difficult for teachers to verify the insights, which could potentially reinforce data biases that misinterpret the abilities of minority students, whilst the massive consumption of data poses a risk of data breaches and compromises children's cognitive privacy.

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