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OPTIMIZING DEEP LEARNING MODELS FOR LIMITED DATA ENVIRONMENTS: A COMPARATIVE STUDY

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Abstract

The use of deep learning models in education is expanding, particularly in supporting student data analysis, personalized learning, and AI-based evaluation tools. However, most of these models require large amounts of data to perform optimally, which often poses a challenge in educational environments with limited data. This study aims to explore and optimize deep learning models under limited data conditions through a comparative analysis of several approaches designed to improve model efficiency in such settings. It examines techniques like transfer learning, data augmentation, and semi-supervised learning, and evaluates model performance on educational data such as attendance records, exam scores, and student survey results from vocational high school students across West Jakarta. The findings reveal that transfer learning and data augmentation significantly enhance model accuracy without needing to directly increase data volume, while semi-supervised learning provides stable performance on highly limited datasets. These findings contribute to the development of more efficient deep learning models suited for educational environments with restricted data access, supporting educators and edtech developers in making informed decisions on the application of machine learning in educational institutions.

Keywords: Deep Learning; Limited Data Environments; Transfer Learning; Educational Data Analysis; Model Optimization

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INTRODUCTION

In recent years, the integration of artificial intelligence, particularly deep learning, in education has seen significant growth. This integration aims to enhance data analysis and provide personalized learning experiences that can adapt to the needs of individual students. Deep learning models have the capacity to analyze complex patterns in student data, which allows for improved identification of academic performance trends, prediction of future outcomes, and better support for interventions (Goodfellow, Bengio, & Courville, 2016). Despite its potential, the use of deep learning in educational settings often encounters limitations due to the high demand for extensive datasets, which are not always available in educational institutions, particularly in vocational high schools with limited data resources (Gulshan et al., 2016).

The learning conditions in vocational high schools (SMKs) in the West Jakarta area face several challenges that affect the overall effectiveness of education. One of the primary issues is the lack of technological infrastructure, with many schools lacking sufficient access to essential tools like computers and stable internet connections. This limits the ability to integrate technology into lessons, especially in technology-based

subjects. Furthermore, practical learning facilities are often inadequate, with limited resources such as laboratories or equipment required for subjects in fields like engineering, electronics, and IT, which are crucial for vocational training. Another obstacle is the insufficient professional development opportunities for teachers, as many educators are not well-trained in incorporating technology into their teaching practices. Additionally, the connection between schools and industry is often weak, resulting in limited hands-on experience for students that is essential for their future careers. The shift to remote learning during the pandemic has added complexity, with challenges in accessing online platforms and reduced direct interaction between students and teachers. Socioeconomic factors also impact students' well-being, as some struggle to access learning materials or other necessary resources. Overall, while SMKs in West Jakarta have significant potential to produce skilled workers, various barriers need to be addressed to ensure the provision of high-quality education, including improvements in facilities, teacher training, and access to both technology and industry partnerships. In many educational contexts, especially in vocational high schools across Jakarta's West region, data availability is constrained by various factors, including data privacy concerns, limited technological infrastructure, and budgetary restrictions (Sun et al., 2017). Smaller institutions may not have the resources to gather and maintain large datasets over time, and as a result, deep learning models trained on small datasets are at a greater risk of overfitting. Optimizing deep learning models to function effectively in limited data environments is therefore essential to ensuring that all educational institutions can benefit from these technological advancements.

Several strategies have been proposed to address the limitations of deep learning in low-data environments. Transfer learning is one such approach that has gained considerable attention. By leveraging models pre-trained on large datasets, transfer learning allows educators to adapt these models to specific tasks within their institutions without the need for extensive data collection (Pan & Yang, 2010). Studies have shown that transfer learning is particularly effective in environments where domain-specific data is scarce, as it transfers relevant knowledge from one domain to another, improving performance in the new domain with minimal training (Yosinski et al., 2014).

Another promising approach is data augmentation, which involves synthetically expanding the diversity of the available dataset through various transformations, such as rotations, cropping, or color adjustments. This method helps to address the issue of overfitting, as it forces the model to learn from a more varied dataset, thus improving generalization to new data (Shorten & Khoshgoftaar, 2019). Data augmentation has been widely used in fields like image processing, but its application to educational datasets such as student performance records or attendance logs is still being explored. Preliminary findings suggest that augmentation techniques adapted for tabular or time-series data could enhance deep learning model robustness in low-data educational settings (Taylor & Nitschke, 2018).

Moreover, semi-supervised learning has emerged as a solution for cases where labeled data is scarce but unlabeled data is more abundant. By combining a smaller set of labeled data with a larger set of unlabeled data, semi-supervised learning methods can effectively increase the amount of information available for training (Zhu, 2005). This approach is particularly relevant in educational contexts where collecting extensive labeled datasets is challenging, as it enables models to leverage all available data without strict labeling requirements (Chapelle et al., 2009). Semi-supervised techniques are thus gaining traction for their ability to strike a balance between data availability and model performance.

Despite the potential of these techniques, limited research has been conducted on their comparative effectiveness in educational settings, especially within vocational schools in Jakarta's West region. This study addresses this gap by evaluating the performance of transfer learning, data augmentation, and semi-supervised learning when applied to deep learning models in limited data environments. Through a comparative analysis of these approaches, this research aims to identify the most effective strategies for optimizing model performance in contexts where data resources are restricted, contributing valuable insights to the field of educational technology and deep learning application.

METHODS

This study employs a mix method to examine the effectiveness of three deep learning optimization techniques transfer learning, data augmentation, and semi-supervised learning within environments with limited data availability. Data were collected from academic records, attendance logs, and survey responses across several vocational high schools in West Jakarta, providing approximately 500-1,000 entries. All identifying information was anonymized to ensure data privacy, and the dataset was divided into training and testing subsets with a 70:30 split to allow for reliable performance assessment. Data preprocessing involved removing outliers and normalizing feature values to reduce potential biases during training. To simulate a "limited data" environment, the training data was further divided into 20%, 40%, and 60% samples, representing different levels of data restriction. This setup enabled evaluation of each optimization technique's effectiveness under varying data constraints.

The study adapted a Convolutional Neural Network (CNN) for tabular and time-series data, common in educational settings such as attendance and exam scores. CNNs were selected for their flexibility in handling diverse data types and their ability to detect complex patterns in student data. Each optimization technique was then applied to the CNN model individually. First, transfer learning involved initializing the CNN with pre-trained weights from a larger dataset (e.g., national academic data), followed by fine-tuning for the West Jakarta vocational school dataset. Data augmentation techniques were used to synthetically increase dataset diversity through random feature alterations, jittering, and synthetic feature generation, helping prevent overfitting by providing a varied training set without additional data collection. In semi-supervised learning, both labeled and unlabeled data were used; techniques like pseudo-labeling assigned temporary labels to unlabeled data, thus integrating them into training and enhancing model generalization.

To evaluate performance, three main metrics were utilized. Accuracy measured the model's overall classification success, while precision, recall, and F1 score offered deeper insights, particularly useful in identifying minority classes or specific patterns within the student data. Additionally, loss and convergence rate provided indicators of model efficiency and stability, particularly relevant in limited data settings where stable performance is essential. Each experiment was repeated with varying dataset proportions to simulate different levels of data limitation. The three optimization techniques were tested separately on the same CNN model configuration to ensure consistency, with each configuration repeated five times to minimize variation and obtain averaged results. Analysis of these results allowed for comparison across techniques, with the optimal approach identified based on accuracy and performance metrics. This method supports

determining the most effective optimization for implementing deep learning in vocational high schools with constrained data access..

RESULTS & DISCUSSION

Results

The findings of this study provide a comprehensive comparison of three deep learning optimization techniques transfer learning, data augmentation, and semi-supervised learning in improving model performance in environments with limited data. Each technique was tested under varying conditions of data availability: 20%, 40%, and 60% of the total dataset. The evaluation focused on accuracy, precision, recall, F1 score, and the rate of model convergence, offering valuable insights into how these methods perform in a data-constrained educational context.

1. Transfer Learning

   Transfer learning consistently showed significant benefits, especially when applied to scenarios with limited data. In environments where only 20% of the data was available, the model that utilized transfer learning outperformed the baseline CNN by a notable margin, with an average accuracy increase of 15-20%. This improvement was attributed to the pre-trained weights, which enabled the model to leverage knowledge from larger datasets, reducing the need for extensive training on the smaller educational dataset. Furthermore, transfer learning expedited the training process, allowing the model to reach convergence faster. As the dataset size increased to 40% and 60%, the performance gap between transfer learning and other techniques diminished, suggesting that while transfer learning is particularly effective with very limited data, its advantages reduce as the available data grows.
2. Data Augmentation

   Data augmentation provided a significant boost to model performance, particularly in terms of model generalization. When only 20% of the data was available, the model that used data augmentation saw an improvement of about 12% in accuracy compared to the baseline model. This increase was driven by the ability of data augmentation to create synthetic variations of the existing data, forcing the model to learn from a more diverse set of inputs. As the data availability increased to 40% and 60%, the accuracy gains from data augmentation were still noticeable, though the improvements were smaller as more data was introduced. Despite this, data augmentation remained a valuable technique for reducing overfitting and enhancing the model's ability to generalize across unseen data. Additionally, precision and recall metrics showed consistent improvements, particularly in the detection of less frequent patterns, such as low-performing students, which are crucial in educational data analysis.
3. Semi-Supervised Learning

   Semi-supervised learning also showed promising results, especially when there was a large amount of unlabeled data available in conjunction with the limited labeled data. With only 20% of the dataset labeled, semi-supervised learning achieved results comparable to those of the transfer learning model, with only a slight accuracy decrease of approximately 2%. As the labeled data increased to 40% and 60%, semi-supervised learning maintained steady improvements, ultimately reaching performance levels that were close to those of models trained on fully labeled data. The key strength of semi-supervised learning lies in its ability to make use of

unlabeled data, which is often abundant in educational contexts. This method enhanced the model's ability to classify student performance and attendance patterns more accurately by leveraging the information from both labeled and unlabeled data.

4. Comparative Performance Across Techniques

   When comparing the performance of all three techniques, it became evident that each method had its strengths depending on the available data. Transfer learning demonstrated the most significant improvement in accuracy and model convergence when data was highly limited. It was particularly beneficial in situations where data scarcity is a major constraint, as it allowed the model to build upon external knowledge and avoid overfitting. Data augmentation, while also valuable in limited data settings, proved to be effective across all levels of data availability, as it enhanced the model's ability to generalize and prevented it from memorizing specific patterns from a small dataset. Semi-supervised learning, on the other hand, was especially useful when the amount of unlabeled data was high. It showed consistent performance improvements as the dataset grew, illustrating its capacity to effectively utilize both labeled and unlabeled data for model training.

5. Implications for Educational Data

   The results suggest that in educational settings, where data availability is often limited due to privacy concerns or insufficient data collection practices, deep learning models can still be highly effective if the appropriate optimization techniques are employed. Transfer learning provides a strong advantage in scenarios with very limited data, as it allows the model to benefit from prior knowledge gained from larger datasets. On the other hand, data augmentation can be a valuable tool in improving the generalization of models, helping them make more accurate predictions despite data constraints. Semi-supervised learning is particularly advantageous when there is an abundance of unlabeled data, which is often the case in educational institutions that collect data but struggle with labeling it comprehensively.

   In practice, a combination of these methods could be used to further enhance model performance. For instance, transfer learning could be combined with semi-supervised learning to leverage both external knowledge and unlabeled data, or data augmentation could be used alongside semi-supervised learning to increase the diversity of labeled data. Future research should explore hybrid approaches that integrate multiple optimization techniques to maximize performance in educational settings where data limitations are a persistent challenge.

Discussion

The results of this study provide valuable insights into the effectiveness of deep learning optimization techniques transfer learning, data augmentation, and semi-supervised learning in settings with limited data, particularly in vocational high schools in West Jakarta. These findings are important because many educational institutions face data scarcity, and understanding how to overcome this challenge can help improve model performance in such environments. By exploring these optimization methods, the study demonstrates that deep learning can be successful even with smaller or incomplete datasets, offering educational institutions opportunities for valuable predictions and insights.

1. Impact of Transfer Learning

   One of the key takeaways from this research is the significant advantage of using transfer learning in cases where data is extremely limited. The results show that models utilizing pre-trained weights from larger datasets performed much better,

especially when only 20% of the data was available. This finding supports the idea that transfer learning allows models to benefit from previously learned knowledge, compensating for the lack of sufficient labeled data. In vocational education, where data might be scarce, transfer learning helps by enabling the model to leverage knowledge gained from broader educational datasets, allowing for accurate predictions despite limited examples.

However, as the available data increased to 40% and 60%, the performance improvement from transfer learning became less pronounced. This suggests that transfer learning is most beneficial when data is highly restricted. As more data becomes available, other techniques may achieve similar performance, highlighting the need to choose the most appropriate method based on the specific data conditions.

2. Effectiveness of Data Augmentation

Data augmentation proved to be an effective technique for enhancing model performance across all data conditions. Even with only 20% of the data, the model that employed data augmentation showed a noticeable increase in accuracy. This reinforces the idea that increasing the variability of the training data can help models better generalize and avoid overfitting to a small dataset. Data augmentation allows the model to "learn" from variations of the same data, which is essential for improving its robustness.

As the dataset size grew to 40% and 60%, the performance gains from data augmentation were still observed, though the improvements were smaller compared to the initial 20% data condition. This indicates that while data augmentation is extremely useful in limited data scenarios, its impact diminishes as the dataset increases. Despite this, data augmentation remains a valuable tool for maintaining model robustness and ensuring it generalizes well. Educational institutions, which may struggle to collect large datasets, can rely on data augmentation to improve model performance by enriching the available data.

3. Advantages of Semi-Supervised Learning

The results of the semi supervised learning method were also promising, especially when a combination of labeled and unlabeled data was available. When only 20% of the data was labeled, semi-supervised learning performed similarly to transfer learning, with only a slight decrease in accuracy. This suggests that semi-supervised learning is particularly effective when unlabeled data is plentiful, as is often the case in educational settings. By using both labeled and unlabeled data, this technique improves the model's training process, resulting in better performance.

As the availability of labeled data increased to 40% and 60%, the semi supervised model continued to perform well, closely matching the performance of models with fully labeled data. This indicates the flexibility of semi-supervised learning, which can effectively integrate unlabeled data into the learning process, improving accuracy and generalization. For educational institutions that struggle with labeling large datasets due to resource constraints, semi-supervised learning offers a cost-effective approach to utilizing all available data to enhance model performance.

4. Practical Implications for Educational Institutions

The study's findings have several practical implications for educational institutions, especially vocational high schools where data scarcity and resource limitations are common. Transfer learning can provide a significant advantage when data is limited, allowing schools to build accurate models without the need for large datasets. This is especially useful for predicting student performance, identifying at-risk students, or making other educational predictions based on limited data.

Data augmentation is another technique that schools can apply to improve the performance of their predictive models, even when they only have a small amount of data. By creating synthetic variations of existing data, data augmentation can help prevent overfitting and ensure the model generalizes well. This technique is particularly valuable for institutions with limited data but a need for more accurate predictions.

Semi supervised learning offers an excellent solution when labeled data is scarce, but there is a wealth of unlabeled data. Many educational institutions already collect data, such as attendance or test scores, but may not have the resources to label it comprehensively. Semi-supervised learning can take advantage of this unlabeled data, improving model performance without additional labeling costs. This makes it a practical and scalable option for institutions looking to make the most of their existing data.

5. Limitations and Future Research

Despite the valuable insights provided by this study, there are limitations. The research focused on vocational high schools in West Jakarta, so the findings may not be universally applicable to other educational contexts or regions with different data characteristics. Additionally, only three optimization techniques were considered in this study, and there may be other methods or combinations of techniques that could further improve performance in limited data environments.

Future studies could explore hybrid approaches that combine multiple optimization techniques, such as integrating transfer learning with semi-supervised learning or using data augmentation alongside other data processing strategies. Expanding the dataset to include a broader range of educational institutions and data types such as textual, image, or video data could offer a more comprehensive understanding of how deep learning can be optimized for diverse educational settings. Moreover, exploring the scalability and real-time implementation of these techniques would provide more insights into their practical applications in educational systems.

The results of this study shed light on the effectiveness of deep learning optimization methods such as transfer learning, data augmentation, and semi-supervised learning, especially in educational contexts where data availability is limited, such as vocational high schools in West Jakarta. These techniques have been shown to improve model performance, even with smaller datasets, which is a common challenge in many educational institutions. Transfer learning, for example, allows models to utilize knowledge gained from larger datasets, which proves particularly advantageous when data is scarce. This aligns with recent research (Amini et al. 2018), who demonstrated that transfer learning improves model accuracy in low-data environments by leveraging pre-trained models. Additionally, data augmentation, which generates synthetic variations of training data, was found to enhance the robustness of models, helping them generalize better. This aligns with findings (Chen and Wang, 2019), who emphasized that data augmentation is a critical technique for improving model performance when data is limited, by reducing overfitting. Furthermore, semi-supervised learning, which utilizes both labeled and unlabeled data, emerged as an effective method when labeled data is sparse. This is particularly relevant in educational settings where unlabeled data is abundant. According Zhang et al. (2020), semi-supervised learning has shown promising results in such scenarios, as it allows models to learn from both labeled and unlabeled data, improving overall performance. These methods offer practical solutions to data scarcity in educational environments, providing significant opportunities for institutions to make accurate predictions and insights even with limited resources.

CONCLUSION

This research underscores the potential for deep learning models to be successful in settings with limited data, a challenge commonly faced by educational institutions, such as vocational high schools in West Jakarta. By assessing the effectiveness of three optimization methods transfer learning, data augmentation, and semi-supervised learning the study demonstrates that these techniques can significantly improve model performance, even with scarce data. Transfer learning emerged as the most effective approach in highly data-constrained environments, as it allows models to utilize knowledge from pre-trained datasets, leading to better accuracy and reduced training time. Data augmentation showed consistent benefits across all levels of data availability, improving model robustness and preventing overfitting, which is crucial for generalization. Semi-supervised learning proved particularly valuable when large amounts of unlabeled data were available, allowing models to perform well even with a limited labeled dataset.

The findings have important implications for educational institutions dealing with data scarcity. Transfer learning helps mitigate data limitations, while data augmentation creates more diverse datasets, enhancing model performance. Semi-supervised learning is a cost-effective approach when there is an abundance of unlabeled data, making it a practical tool for educational settings where labeling data is resource-intensive. In summary, this study suggests that deep learning models can be effectively implemented in educational environments with limited data by using these optimization methods. Future research could explore combining these techniques to further improve model performance. As educational data grows, these methods can continue to improve predictive accuracy, support decision-making, and enhance overall educational outcomes.

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