The object of this research is the performance of air transportation vocational education. The problem in this research that must be solved is the complexity of the model in machine learning which requires a long processing time and requires high resources, so the knowledge transfer process in knowledge distillation must be carried out carefully so that the student model can capture and reproduce knowledge from the teacher's model. without loss of accuracy and problems such as Good Corporate Governance, Organizational Flexibility, and Strategic Change Management variables, which are interrelated and difficult to model accurately. The results obtained are in the form of a model that can predict vocational education performance by utilizing machine learning and knowledge distillation. The interpretation of this research is to apply the XGBoost machine learning algorithm and knowledge distillation. The characteristics and characteristics obtained are that the teacher model has the best performance in terms of loss, while the student model with distillation shows a significant reduction in loss compared to training without distillation. Thus, the distillation process is proven to help student models capture knowledge from teacher models, producing prediction accuracy of up to 90 % and being an efficient alternative in predicting the influence of main factors on the performance of air transportation vocational education. These findings are expected to provide a significant contribution to the development of more efficient and effective prediction models in the context of vocational education, especially in the field of air transportation

Keywords: strategic change management, knowledge management, organizational performance, machine learning, knowledge distillation

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IMPLEMENTATION OF KNOWLEDGE DISTILLATION IN DEVELOPING A PREDICTION MODEL TO KNOW THE PERFORMANCE OF AIR TRANSPORTATION VOCATIONAL EDUCATION USING MACHINE LEARNING

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1. Introduction

In the world of the transportation industry, it cannot be separated from the continuity of technology which is increasingly developing in doing things such as making predictions, identifying and classifying in the context of machine learning. In this context, vocational education in the field of air transportation has a big responsibility to prepare professional staff who are technically skilled and have the ability to adapt to management and technology [1, 2]. In vocational education, institutional performance is greatly influenced by a number of factors, including Good Corporate Governance, Organizational Flexibility, and Strategic Change Management [3, 4]. These three factors are the key to improving organizational performance in facing global challenges and growing industrial needs. Good Corporate Governance (GCG) in the context of air transportation vocational education is an effort to ensure that educational institutions are managed ethically, transparently and accountably. Organizational Flexibility plays an important role in determining the success of air transportation vocational education institutions and the third factor which is no less important is Strategic Change Management (SCM), namely the institution's ability to manage sustainable strategic change. In the era of technological disruption, vocational education in the air transportation sector must be able to adapt quickly to industry changes, starting from adopting new technology, curriculum development, to improving the skills of teaching staff [5, 6]. In making changes to educational institutions to resolve performance problems, risk mitigation needs to be implemented by utilizing machine learning which can analyze and identify changes and can predict their impact on performance. With data-based analysis, educational institutions can determine the most effective change strategies that suit internal conditions and external demands [7, 8].

The problems faced in this research include the complexity of the model in machine learning, which can be seen from the long processing time, large resource requirements, and the complexity of the variables studied, such as the influence of

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Good Corporate Governance, Organizational Flexibility, and Strategic Change Management [9]. These variables are interconnected and difficult to model precisely. In addition, the knowledge transfer process in knowledge distillation needs to be applied to all architectures so that the student model can understand the data patterns in the teacher model [10]. This research applies knowledge distillation techniques to optimize a prediction model for the influence of Good Corporate Governance, Organizational Flexibility, and Strategic Change Management on the performance of air transportation vocational education. By reducing model complexity without sacrificing accuracy, educational institutions can perform real-time performance predictions, enabling faster and more informed decision making. This is especially crucial in the context of vocational air transport education, where strategic decisions often have to be taken immediately due to changes in industry conditions or urgent regulations [11, 12].

Therefore, research aimed at this development becomes relevant research by optimizing the application of Machine Learning with the XGBoost and knowledge distillation algorithms in measuring the effectiveness of vocational education performance as the focus of research. This research aims to develop a new approach in predicting and optimizing the performance of air transportation vocational education through the application of machine learning and knowledge distillation [13, 14]. Factors such as Good Corporate Governance, Organizational Flexibility, and Strategic Change Management are analyzed in depth to understand their impact on the performance of educational institutions. With distillation techniques, machine learning models can be simplified without reducing accuracy, thereby enabling faster and more efficient predictions [15, 16]. In addition, the integration of Knowledge Management as a mediating variable provides additional insight into how knowledge can be used to strengthen organizational performance in facing dynamic industrial challenges.

2. Literature review and problem statement

Research [17] shows that a predictive model based on knowledge distillation was successfully developed to support data clustering and visualization with an accuracy rate of up to 93 %. However, the main challenge faced is related to the extraction of knowledge graphs in certain domains, such as parameters in determining facial identification on algorithm performance. The main difficulty lies in building a credible domain-based embedding framework to map knowledge sources and inter-domain knowledge relations. One potential approach to overcome this challenge is the application of graph queries using machine learning in modeling the relationships of these variables. This shows the importance of integrating knowledge distillation techniques with graph query-based approaches to improve the effectiveness of prediction models in the context of vocational education.

Research [18] shows that the results of this research are a prediction model for government performance using data from key performance indicators. However, there are unresolved problems in grouping variables using artificial neural networks in the context of public policy evaluation, which causes errors in classification due to the difficulty of modeling the complexity of relationships between time and non-time factors. One way to overcome this challenge is through the application of knowledge distillation that utilizes machine learning, which can increase accuracy and correct analytical weaknesses.

Research [19] produce a model to predict the performance of supervised learning algorithms in tracking discussion trends related to crimes committed on digital platforms. However, there are unresolved issues in accurately extracting information from complex data reviews. This research faces difficulties in utilizing supervised learning techniques to efficiently detect patterns associated with fraudulent activities. One approach that can overcome this challenge is to integrate machine learning models with knowledge distillation which is able to identify and group patterns in training data to strengthen the prediction model architecture. This shows that the use of machine learning with knowledge distillation is highly recommended to improve the performance of supervised learning algorithms.

Research [20] produces a model that is able to predict educational performance by considering various variables, but there are unresolved problems related to the time complexity of managing educational data. These problems include inaccuracies in the analysis of educational variables, such as teaching methods, attendance rates, and learning outcomes, as well as low data processing efficiency, making reliable predictions difficult. One approach to overcome this challenge is to utilize machine learning methods integrated with mathematical graph query models. This approach can optimize educational performance analysis in the short term, for example for monthly evaluations, to the long term for annual planning, taking into account factors such as resource allocation, curriculum and student participation levels. All of this shows that the application of machine learning with knowledge distillation is highly recommended to improve holistic predictions of educational performance.

Research [21] resulting in innovative strategies that combine machine learning and predictive analytics approaches to predict crime. However, there are problems that have not been resolved, namely limitations in criminal risk management which still relies on historical and post-incident data analysis, so it is less able to detect and respond to threats in real-time. This approach involves the use of time series analysis and anomaly detection to identify crime patterns, as well as natural language processing to analyze incident reports or descriptions. Additionally, prediction models are continuously improved through machine learning algorithm updates to ensure accuracy in anticipating criminal activity in dynamic environments. By leveraging mathematically based graph query models, the relationship between predictive analytics, machine learning and crime patterns can be mapped more effectively, supporting predictive flexibility and rapid response to potential threats. All of this shows the importance of applying machine learning with knowledge distillation to improve crime prediction capabilities.

Research [22] resulting in an innovative strategy that combines machine learning and predictive analytics approaches to improve the performance of traffic detection sensors. However, there are unresolved problems, namely limitations in predicting traffic jams in real-time, because the current model still relies on historical and post-event data analysis. This approach involves time series analysis and anomaly detection to identify unusual traffic patterns, as well as the application of natural language processing to understand descriptive data regarding road conditions. In addition, sensor performance models are continuously improved through machine learning algorithms that are able to adapt to changing traffic patterns. By applying machine learning with knowledge distillation, the relationship between sensor data, predictive analysis and machine learning can be mapped more effectively, increasing prediction accuracy and traffic detection efficiency. All this shows that the use of machine learning with knowledge distillation is highly recommended to optimize the performance of traffic detection sensors.

Research [23] generate complex query models to predict company performance by considering temporal parameters and hierarchical patterns. However, this research still faces problems because the method used focuses on static knowledge graphs, thereby ignoring semantic information related to the time dimension, such as changing trends in profitability, operational efficiency, and market dynamics. To overcome this problem, the semantic relationship method with knowledge distillation will be applied which is able to study time and quantity constraints accurately in analyzing company performance data. This method also utilizes manual rules to strengthen accuracy in the interpretation of related parameters. This shows that the application of machine learning with knowledge distillation is highly recommended to achieve the goal of implementing knowledge distillation and implementing machine learning algorithms to improve predictions of company performance in a holistic and responsive manner to changes in the business environment.

3. The aim and the objectives of the study

This research aims to be a process model for identifying parameters such as good corporate governance, organizational flexibility, and strategic change management on the management performance of the Ministry of Transportation's Air Transportation Vocational Higher Education using machine learning.

To achieve this aim, the following objectives are accomplished:

– implementing knowledge distillation to be able to see the impact of vocational education performance;

– implementing machine learning algorithms.

4. Materials and methods

The object of this research is the performance of air transportation vocational education. In this context, this study uses analytical methods to apply machine learning models in making predictions to be able to determine the influence of Good Corporate, Organizational Flexibility and management strategies on the performance of air transportation vocational education. This research uses the XGBoost algorithm which then be optimized by distilling knowledge with indicators relevant to organizational flexibility, strategic change management, and the performance of air transportation vocational education institutions. Data is collected systematically using questionnaires and from reports from related agencies, then preprocessing is carried out to limit incomplete data, normalization and feature recognition, then the data is divided into training data and test data with appropriate proportions. In this study, it is assumed that the data used reflects the actual conditions of air transportation vocational education institutions, and the relationship between variables is linear or can be mapped effectively by the XGBoost algorithm. Simplification is done by limiting the number of indicators for each main variable (Good Corporate Governance, Organizational Flexibility, and Strategic Change Management) so that it is not too complex, but still represents the main aspects of each variable. The main output of this study is an XGBoost-based machine learning model that is able to predict the performance of air transportation vocational education institutions based on Good Corporate Governance, Organizational Flexibility, and Strategic Change Management. Additional outputs include model evaluation reports, such as accuracy, precision, recall, ROC-AUC curves, and confusion matrices, which provide a comprehensive picture of model performance. This study also produces data-based recommendations to improve institution performance through significant indicators from model results. This research will use hardware such as a laptop with Windows 10 specifications with a Core i5 processor and software such as Microsoft Word and the use of python programming. ROC-AUC curve evaluation technique and confusion matrix to see the results of machine learning models with the XGBoost algorithm and the application of knowledge distillation. This research will begin by designing the architecture as shown in Fig. 1 below.

Fig. 1 will explain that in making predictions it is possible to use a machine learning model that uses the XGBoost algorithm and the application of knowledge distillation, in this context it requires data that is structurally sound and then wit is possible to use the XGBoost algorithm with the following mathematical formulation:

$$y_i = \sum_{k=1}^{K} f_k\left(x_i\right). \tag{1}$$

In (1), y_i is the final prediction for the variable i and $f_k(x_i)$ is the result of a decision k to the data x_i which then K is the total of all decisions in the ensemble. Then use this algorithm to minimize. The loss function is to determine the prediction error and complexity of a prediction model which contains the following equation (2):

$$L(\Theta) = \sum_{i=1}^{n} l\left(y_i, \hat{y_i}\right) + \sum_{k=1}^{K} \Omega\left(f_k\right). \tag{2}$$

$L(y_i)$ is a loss function variable between the target value symbolized by y and predicted value with symbols i. $\Omega(f_k)$ is a symbol for controlling the complexity of the model with the formulation in equation (3):

$$\Omega\left(f_k\right) = \gamma T + \frac{1}{2}\lambda \|w\|^2. \tag{3}$$

In (3) it is possible to determine the training process for the XGBoost algorithm using the gradient descent approach to improve predictions and minimize errors from the previous model, which T number of decision trees. After that, knowledge distillation will be applied with teacher model training with equation (4):

$$f_{teacher} = dataset\left\{\left(x_i, y_i\right)\right\}_{i=1}^{n}. \tag{4}$$

P are similarities between 4 models, teachers will use symbols f which will interpret complex configurations on a lot of training data which will produce predictive output $Z_{teacher}$ for each data. On each prediction of the symbol $Z_{teacher}$ will be used as a soft target in conducting training on student models which are the output of $Z_{teacher}$ will be processed with equation (5):

$$P_{teacher}\left(x_1\right) = soft\max\left(\frac{z_{teacher}\left(x_i\right)}{T}\right). \tag{5}$$

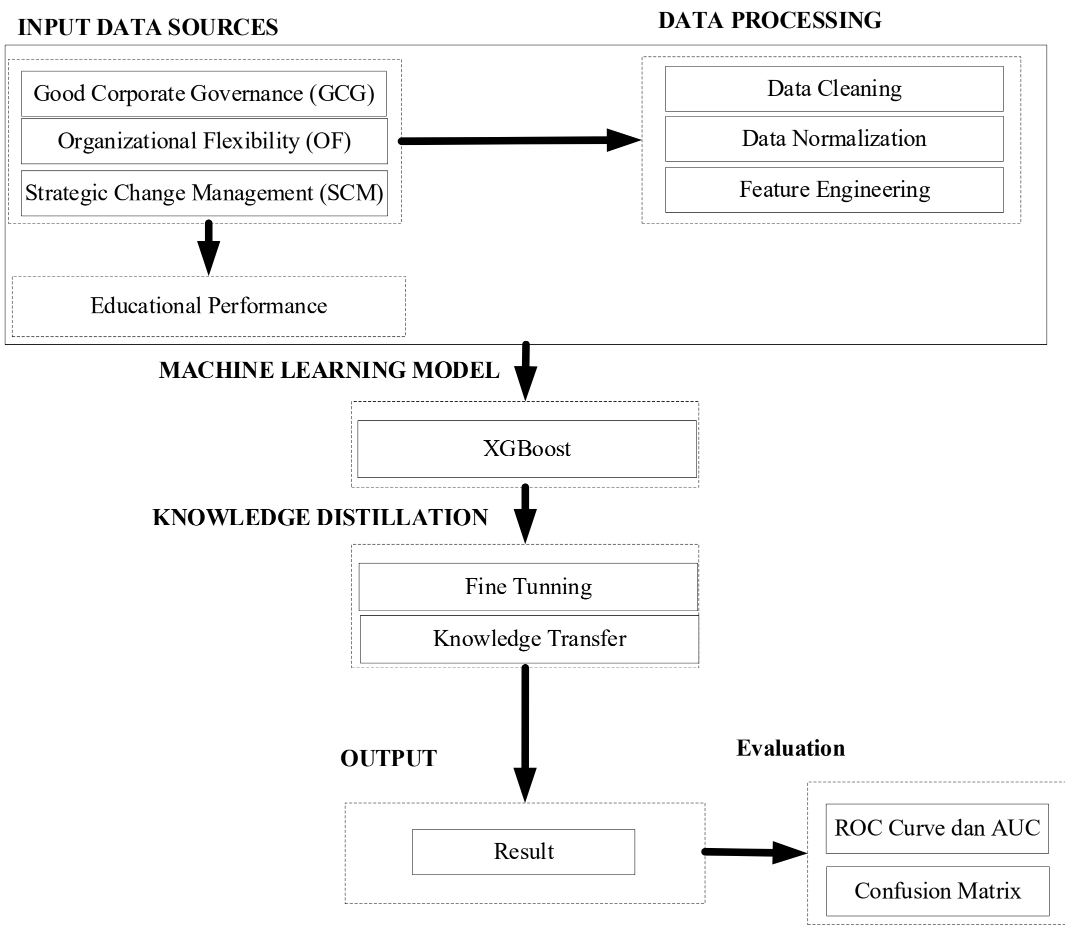

Fig. 1. Architectural framework

In (5) there will be a symbol T which is a variable to control the smoothness of the data learning process from the prediction model. Where on $f_{student}$ will be processed using models from soft target teacher and hard target or original labels from the data which will produce equation (6):

$$L_{student} = \alpha \cdot L_{soft}\left(P_{student}, P_{teacher}\right) + \\ +(1-\alpha) \cdot L_{hard}\left(P_{student}, y_i\right). \tag{6}$$

In (6) it is possible to combine the loss function and $L_{students}$ then there will be a symbol L_{soft} for predictions $P_{student}$ and soft targets $P_{teacher}$. Then applying knowledge distillation to the XGBoost algorithm will produce a mathematical formulation in equation (7):

$$L_{student} = \alpha \cdot \sum_{i=1}^{n} KL\left(P_{student}\left(x_i\right) \| P_{teacher}\left(x_i\right)\right) + \\ +(1-\alpha) \cdot \sum_{i=1}^{n} l\left(y_{i,} y_{student}\left(x_i\right)\right). \tag{7}$$

In (7) there $KL(P_{students}||P_{teacher})$ which used to measure distribution differences in the student model and teacher model or can be called using the Kullback-Leibler divergence technique and $l(y_i, y_{student}(x_i))$ is a symbol used to evaluate student models in terms of error values and in this study it is possible to confusion matrix evaluation and ROC-AUC values.

5. Results of the knowledge distillation model for machine learning based predictions

5. 1. Application of the knowledge distillation model

The application of knowledge distillation in this research aims to increase the efficiency of the student model by studying knowledge that has been processed by a more complex teacher model. This research will transfer knowledge from the teacher model to the student model so that it can be used and processed more easily. In the process, soft labels will be used, which are the results of a probabilistic teacher model from real data which is carried out by combining hard losses and then training the student model with real data. The following is the mathematical formulation resulting from the application of the knowledge distillation model at the training stage in (8):

$$\min{}_{f.student}^{L_{total}} = \\ = \min{}_{f.student} \left(\begin{array}{l} \alpha \cdot \dfrac{1}{N} \sum_{i=1}^{n} P_{teacher}\left(y \mid x_i\right)^{(T)} \times \\ \times \log \left\| \left(\dfrac{P_{student\left(y|x_i\right)^{(T)}}}{P_{student\left(y|x_i\right)^{(T)}}} \right) + (1-\alpha) \cdot L_{CE} \end{array} \right). \tag{8}$$

The mathematical expression from (8) is the loss function in knowledge distillation, which aims to train the student model to imitate the larger teacher model. The total loss function with the symbol L_{total} combines two components of the distillation loss, which measures the closeness of the output probability distribution between the student and teacher models, and the cross-entropy loss with the symbol L_{CE} that ensures the student model is able to predict the true label. The parameter α regulates the balance between the two components. This approach helps the student model to be efficient without losing significant accuracy. then be implemented on data on good corporate governance, organizational flexibility, and strategic change management related to the performance of air transportation vocational education using machine learning. Implementation is carried out to see the results of knowledge distillation in making predictions. Based on formulation (8), a graph is produced as in Fig. 2.

Fig. 2 shows a comparison of the loss values in the knowledge distillation model between the teacher model, the student model which was trained by distillation and the student model which was trained with standard parameters which resulted in the teacher model having the best performance in terms of loss with a lower value because it has a better architecture. More complex, whereas the student model with distillation produces a significant reduction in loss, while the student model with normal training has a higher loss compared to the distillation model, which concludes that the distillation process helps the student model capture better knowledge than the teacher model. Then, after the loss value process in the knowledge distillation model, there will be a prediction model to predict whether there is an influence between Good Corporate Governance, Organizational Flexibility, and Strategic Change Management on the performance of air transportation vocational education. The prediction model produces the predictions in Fig. 3 below.

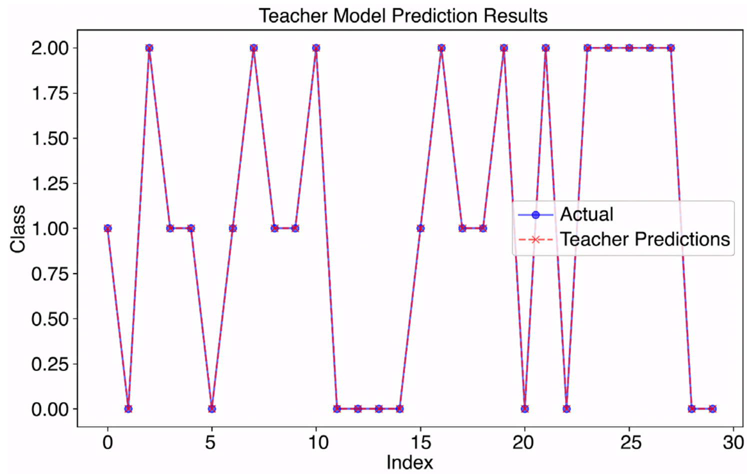

Fig. 3. Prediction teacher model results

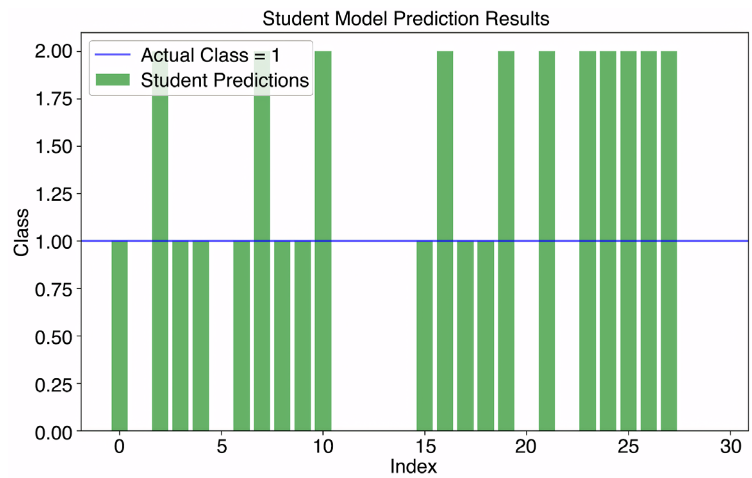

Fig. 4. Prediction student model results

Fig. 3 will explain that in the application of knowledge distillation there will be a teacher model that carries out the prediction process so as to produce actual and predicted values. Then there will be a student model for making predictions in Fig. 4.

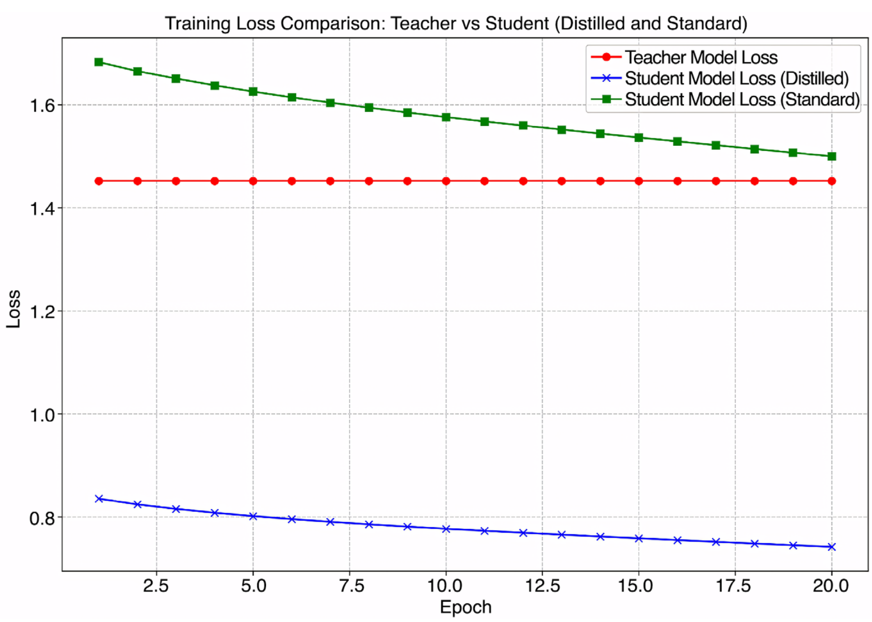

Fig. 2. Comparison of loss values in the knowledge distillation model

In Fig. 3, 4, it is explained that there are teacher models and student models in making predictions related to approaches in the context of knowledge distillation, namely the process of transmitting knowledge from the teacher model to the student model. In general, the teacher model is a complex model that has a large architecture with a fairly good level of accuracy that functions as a source of knowledge in training small student models and is designed to be more efficient in terms of computing. In the training process, the student model will be processed in running parameters to imitate the output or predictions of the teacher's model so that it can achieve close performance. The results in Fig. 3 explain that the results of the student model succeeded in achieving similarity to the teacher's model with an accuracy level of 90 percent, where there is a probability distribution that the student model output has the same pattern as the teacher. model so that the distillation process is successful, and the student model can be used as a better alternative.

efficient for predicting the influence of Good Corporate Governance, Organizational Flexibility, and Strategic Change Management on the performance of air transportation vocational education.

5. 2. Comparison of machine learning models

In this context, a comparison of machine learning models will be carried out regarding the application of knowledge distillation in the context of optimizing predictions of the influence of Good Corporate Governance, Organizational Flexibility, and Strategic Change Management on the performance of air transportation vocational education. In this case, it is possible to optimize and combine machine learning models. In this research, the XGBoost algorithm will be used as a basic model that functions to explore complex relationships between variables. When using XGBoost, it is possible to use a boosting technique to increase prediction accuracy by minimizing the loss function through iterative learning. In its application, the XGBoost algorithm displays results with very good performance, but there are challenges and shortcomings of the model applied, such as processing time complexity and the number of architectures to be modeled. So then the model comparison is carried out by applying knowledge distillation which will transfer knowledge from the very complex XGBoost model to a smaller and more efficient model. The following are the comparison results of the application of the machine learning algorithm in Fig. 5.

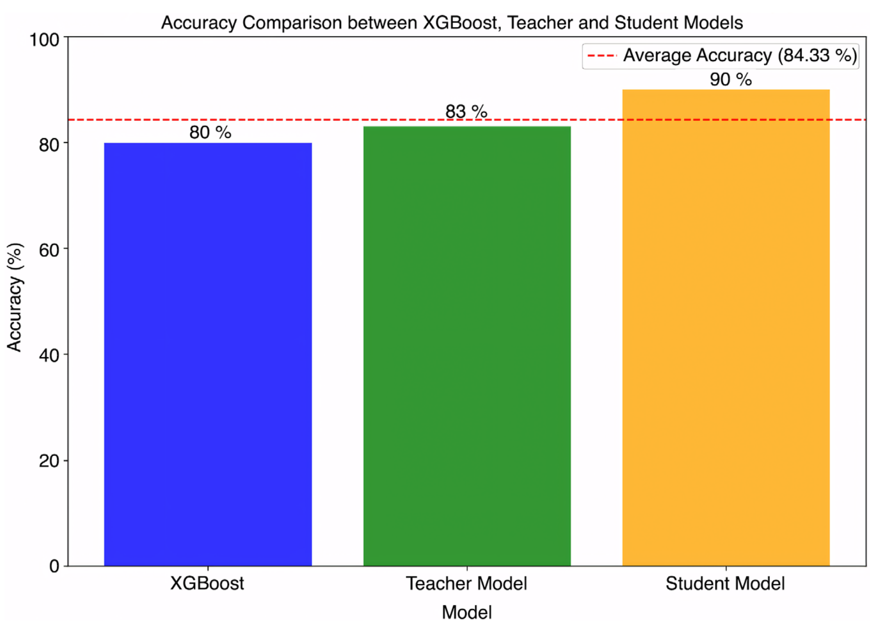

Fig. 5. Comparison of machine learning models

The caption in Fig. 5 will explain the results of the XGBoost algorithm and the teacher model, student model of knowledge distillation. The student model will carry out training and imitate all the parameters in the XGBoost algorithm model to make the same predictions. Fig. 5 shows the results that the efficient student model increases accuracy compared to the XGBoost model. Applying knowledge distillation in this context provides multiple benefits and the distillation process allows organizations to reduce operational costs associated with processing large amounts of data, without compromising the quality of the predictions produced. In Fig. 5, the accuracy of XGBoost is 80 % in making predictions and the teacher model in the knowledge distillation context is 83 % and then the student model is 90 %. So, it can be concluded that the student model has the best performance among the three models. This shows that the knowledge distillation process succeeded in increasing the accuracy of the student model compared to the teacher model and the XGBoost baseline model.

6. Discussion of knowledge distillation and machine learning models to determine educational performance

In the context of the discussion, it is possible to emphasize the novelty and significance of research through the implementation of knowledge distillation in developing performance prediction models for air transportation vocational education. All components of supporting evidence, such as application of algorithms, use of distillation models, and calculation of model results, are arranged systematically. This research aims to answer key discussion questions regarding the efficiency and accuracy of predictions using knowledge distillation techniques. This research produces a prediction model that utilizes knowledge distillation by combining soft labels and hard loss. The distillation process is carried out by transferring possible outputs from the teacher model (large model) to the student model (smaller and more efficient model), as shown in formulas (6)–(8). The results of the prediction model are visualized in Fig. 3, 4, where the student model achieves a prediction accuracy of 90 %, higher than the teacher model which only reaches 83 %. This shows that the distillation technique is able to increase prediction accuracy with lower computing resources. This knowledge distillation method provides an alternative solution to the weakness of the Extreme Gradient Boosting (XGBoost) algorithm used as the basic model, namely high computational complexity. Compared with other studies such as [24], which uses neural networks to predict quality of life, knowledge distillation is able to overcome the complexity of the model without sacrificing efficiency.

In contrast to the approach in [24], where neural network models have high complexity in training, the results of this study show that knowledge distillation allows smaller student models to achieve better performance (90 % vs. 83 % in teacher models).

In comparison with research conducted by [22, 23], it shows the effectiveness of machine learning in identifying and predicting with algorithms such as random forest and SVM providing more accurate results than traditional regression methods. However, its weaknesses include the lack of analysis of external factors such as macroeconomic trends, limitations in handling outliers, and a limited focus on popular algorithms without exploring other methods such as deep learning. This is made possible by effective knowledge transfer through soft labels and concurrent training using real data (hard labels). With this approach, the complexity of the XGBoost algorithm, which was previously a major obstacle, can be minimized more efficiently. Through the results achieved, this research proves that the main goal of developing an efficient and accurate prediction model has been achieved. The problem identified, namely the need for a model that saves resources while maintaining performance, was successfully resolved through a knowledge distillation approach. This evidence is strengthened by the prediction results in Fig. 3, 4 as well as the comparison of accuracy between teacher and student models. The limitations of this research are that the knowledge distillation technique shows good results in the context of air transportation vocational education performance, but the generalization of these results to other domains requires further testing and Disadvantages of the Student model, although efficient, still requires high-quality initial data and intensive training to achieve maximum accuracy.

The proposed solution provides significant practical impact, especially in reducing operational costs related to big data processing without sacrificing prediction accuracy. However, application on a broader scale requires additional evaluation of the suitability of the student model in dealing with data with high variability. The application of this knowledge distillation proves efficiency in developing prediction models, filling a gap in the literature regarding the integration of machine learning for air transportation vocational education. Thus, this research not only provides practical solutions but also enriches theory in the fields of machine learning and organizational performance management.

7. Conclusions

1. This research succeeded to implementing knowledge distillation to develop a prediction model to determine the performance of air transportation vocational education using machine learning. The results obtained show that the prediction model developed using the knowledge distillation method is able to produce high accuracy, with optimal performance on test data compared to the standard model without distillation. A distinctive feature of the results of this research is the efficiency achieved in the use of computing resources without sacrificing prediction accuracy. This contributes to resolving some of the problems identified, such as the need for a model that is lightweight but still precise in supporting the performance evaluation of air transportation vocational education. Compared with other methods summarized in the literature review, these results can be explained by the application of a distillation process that allows the transfer of knowledge from a large model (teacher model) to a smaller model (student model) effectively, thereby maintaining performance without requiring large resources.

2. The evaluation results show that the student model is able to achieve prediction accuracy of 90 %, higher than the teacher model (83 %) and the XGBoost baseline model (80 %). Thus, implementing knowledge distillation not only improves accuracy but also reduces operational costs associated with big data processing. This research can increase the potential of knowledge distillation as an effective method for optimizing machine learning models in diverse contexts, especially in the fields of education and management.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

Financing

The study was performed without financial support.

Data availability

Manuscript has no associated data.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the currrent work.

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