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DEVELOPMENT OF LEARNING MODELS BASED ON MACHINE LEARNING WITH QUANTUM ANNEALING FOR LEARNING OPTIMIZATION IN THE DIGITAL ERA

The object of this study is the prediction of digital learning achievement. The problems solved in this study are the low accuracy and efficiency of the prediction model caused by the complexity of the learning data and the limitations of conventional tuning methods such as grid search and random search which are unable to optimally navigate the wide and non-linear parameter space. The results obtained show that the integration of quantum annealing into the hyperparameter optimization process can significantly improve model performance. Model accuracy increased from 82% to 91%, with consistent improvements in precision, recall, and F1-score. The model also showed faster convergence and lower losses on both training and testing data, indicating better generalization capabilities to new data. Interpretation of these results concludes that quantum annealing can navigate the parameter space efficiently, exploring combinations of values that are unreachable by conventional methods. The main feature and characteristic of these results lies in its ability to combine the computational efficiency of LightGBM with the exploration of complex solutions through quantum methods, making it very suitable for dynamic learning problems. The scope and conditions of practical use of the developed model include digital-based learning management systems, adaptive learning platforms. These findings are relevant to be applied in the development of artificial intelligence-based education systems that support personalization in the current era of digital transformation

Keywords: machine learning, hyperparameter tuning, complexity of quantum annealing, optimization digital transformation

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1. Introduction

The transformation of education towards the digital era has presented new opportunities and challenges in the learning process. Although various digital platforms such as learning management systems have been widely implemented, most are still static and unable to adjust the learning approach to the individual needs of students [1]. This inequality raises serious problems, especially in terms of the effectiveness and equity of learning outcomes. On the other hand, educational institutions now have access to abundant and diverse learning activity data, but it has not been optimally utilized to support data-based decision making [2, 3]. The problem becomes more complex when the very large and diverse learning activity data is not utilized optimally, even though the data has great potential to produce accurate learning achievement prediction models, starting from forum participation data, quiz results, material interactions, learning duration, to cognitive evaluations. However, educational institutions currently still have difficulty building adaptive predictive models due to limitations in managing big data, identifying hidden patterns, and overcoming the uncertainty of student learning performance caused by various external factors such as socio-economic conditions, technological disruptions, or mental health issues [4, 5]. Machine learning has emerged as one of the intelligent approaches that is able to identify patterns from learning data automatically and predict student learning outcomes individually. Neural Network is a learning model that can be built to provide adaptive recommendations, detect the risk of academic failure, and suggest early intervention [6]. There are shortcomings in ML algorithms that are highly dependent on the right hyperparameter optimization process, where finding the best parameter combination is a complex process that requires high computation time and is prone to overfitting or underfitting problems. For this reason, a more efficient and accurate hyperparameter optimization method is needed, one of which is the quantum annealing approach [7]. Quantum annealing is an optimization method based on quantum mechanics principles that is able to explore the solution space more widely and efficiently than classical methods such as grid search or random search. This technique is designed to find global solutions in high-complexity combinatorial optimization problems, and has shown promising results in various industrial applications [8, 9].

In the context of learning prediction, quantum annealing can be utilized to optimize the configuration of machine learning models more quickly and accurately, thereby reducing training time and increasing the precision of student learning outcome predictions [10]. The integration of machine learning and quantum annealing in education has great potential to create an adaptive, precise, and data-driven learning system that is automatically able to adjust learning strategies to the conditions and needs of each student. With this approach, educational institutions can make maximum use of learning activity data to build models that are able to predict learning outcomes, recommend materials, and identify students at risk of academic failure earlier and more precisely [11, 12]. These studies comprehensively identify key variables of digital learning activities, such as participation rate, interaction duration, and response to materials, which are then processed into input for artificial intelligence-based prediction algorithms. These studies also offer contributions in improving the effectiveness of technology-based learning, increasing the efficiency of decision-making processes in education, and supporting the ongoing digital transformation of education. The uniqueness of these studies lies in the application of quantum computing technology, which has so far been used more in the fields of logistics, finance, and bioinformatics, into a relatively new educational realm [13, 14].

Optimizing learning in the digital era has become a very relevant scientific issue considering the rapid development of educational technology and the increasing need for adaptive, efficient, and personalized learning systems. Amid the increasing complexity of digital learning data, predictive approaches based on artificial intelligence are crucial to identify student learning patterns and adjust teaching strategies in real-time. The relevance of this issue is also reinforced by the global demand for education that is responsive to individual needs, as well as the limitations of conventional learning models in handling the diversity of learning behaviors. In this context, the integration of machine learning and quantum computing, especially quantum annealing, is a strong foundation for presenting predictive solutions that are not only accurate but also efficient on a large scale.

Therefore, studies that are devoted the integration of machine learning and quantum annealing is relevant for concrete solutions to the problem of learning prediction in the complex digital era. The results of these studies will provide important contributions in designing appropriate learning recommendation systems, accelerating the transformation of digital education, and strengthening data-based academic decision-making support systems.

2. Literature review and problem statement

Research [15] applied classification techniques such as decision trees and support vector machines to classify students' achievement levels based on their demographic data and interactive behavior during the online learning process. The model built in the study showed moderate accuracy and successfully captured some of the basic patterns of the learning data. However, there are unresolved issues related to the limitations of the model's performance due to the lack of optimal hyperparameter tuning. The reasons for this may include objective difficulties in exploring complex and high-dimensional parameter spaces. To overcome this difficulty is to use an optimization method that is able to explore the parameter space efficiently and find the optimal configuration in a shorter time. This approach has been used in other fields through the application of quantum annealing. So, all of this shows that implementing the integration of machine learning algorithms with quantum annealing produces a learning achievement prediction model that is not only accurate and adaptive.

In research [16], implementing hyperparameter optimization in deep learning models for educational data mining, using classical grid search approach and random search technique. Experiments conducted show that although these methods are able to improve model performance compared to default settings. In developing machine learning-based learning models, the hyperparameter tuning process is a crucial step that affects the final performance of the model. Common approaches used, such as grid search and random search, although widely applied, have significant limitations. The main problem lies in the high computational cost and execution time required, especially when dealing with large and complex parameter spaces. The brute-force method used in these approaches is inefficient, because it explores all possibilities without intelligent strategy selection. Approaches such as quantum annealing have been used in various optimization domains due to their ability to find global solutions in faster time with higher resource efficiency. So, the integration of machine learning techniques and quantum annealing methods can optimize hyperparameters in learning outcome prediction models.

In research [17] applied a hybrid approach using light gradient boosting machine (LightGBM) and Bayesian optimization to predict the potential for students to drop out of school. This study shows that LightGBM is very efficient in handling large-scale tabular data and has good predictive ability in the context of education. However, there is an unresolved problem related to the limitations of the search space in Bayesian optimization which is local in nature, so it has the potential to miss the optimal configuration in a complex and multi-peak (multi-modal) parameter space. To overcome these limitations is to apply a global optimization technique that is able to explore the parameter space thoroughly and efficiently. Quantum annealing, as a quantum mechanics-based optimization method, has been proven effective in solving large-scale combinatorial optimization problems through a global exploration approach to the solution space. So, the integration of LightGBM with quantum annealing as an alternative global hyperparameter tuning method can improve the quality of predictions in the education system.

Research [18] simulated annealing algorithm to solve combinatorial optimization problems in educational environments. The results show that this algorithm is able to effectively avoid local minimum traps, especially in tasks such as complex scheduling and assessment. However, there is an unresolved problem related to the relatively high convergence time of simulated annealing. The main reason for this is the explorative nature of the algorithm which requires many iterations to reach the optimal solution, thus requiring large computational resources and inefficient processing time to be applied in real-time or adaptive digital education systems. To overcome this limitation is to utilize optimization methods inspired by the principles of quantum mechanics, such as quantum annealing, which has been proven to be able to offer faster convergence and wider and more efficient exploration of the solution space. Thus, integrating quantum optimization methods such as quantum annealing into machine learning-based learning models in the context of education is very much needed.

In research [19] the use of quantum annealing as an optimization technique for model parameter tuning in various domains, such as logistics and energy systems. In the study, the authors reformulate the hyperparameter optimization problem into the form of quadratic unconstrained binary optimization (QUBO), then solve it with the help of the D-Wave quantum processor. The results obtained show that quantum annealing is able to find the global minimum efficiently, even in complex and high-dimensional parameter spaces. There is an unresolved problem, namely the limited application of quantum annealing in the context of education, especially for hyperparameter tuning in predictive models of digital learning. To overcome this problem, quantum annealing was applied to the existing educational machine learning framework, and tested directly in the case of predicting learning outcomes based on student behavior data.

In research [20], development of predictive models for adaptive learning platforms by utilizing deep learning approaches and real-time student behavior data. This model is designed to adjust the learning process based on actual student interactions with the system, and has been proven to achieve a high level of prediction accuracy. However, there are unresolved issues related to the hyperparameter tuning process which is still done manually. This manual approach is not only time-consuming and resource-consuming, but also risks producing suboptimal configurations, especially in complex and dynamically changing learning environments. to overcome these limitations is to integrate automatic and intelligent optimization strategies in the hyperparameter tuning process. So, integrating quantum annealing in the hyperparameter optimization process for predictive models on adaptive digital learning platforms can overcome these problems.

In research [21], application of ensemble learning framework to predict student engagement level in massive open online courses (MOOC) platform. In this approach, several machine learning models are combined to improve the prediction accuracy of student participatory behavior, such as frequency of accessing materials, participation in forums, and completion of assignments. However, there is an unresolved problem, namely the difficulty in determining the optimal configuration of hyperparameters of the combined models. Complexity increases with the increasing number of models in the ensemble, making the parameter selection process a major challenge that directly impacts the final performance of the system. to overcome this difficulty is to treat hyperparameter selection as a global optimization problem and implement it through a more robust and efficient method with quantum annealing emerging as an alternative approach that is able to explore the solution space widely and find the optimal configuration faster than classical optimization methods. quantum annealing, which is formulated through the quadratic unconstrained binary model.

All this allows to assert that it is expedient to conduct a study on the integration of the quantum annealing method in the ensemble learning framework for educational predictive systems is highly recommended.

3. The aim and the objectives of the study

The aim of this study is to develop a learning model that can be predicted accurately based on student digital data using a machine learning approach with optimization through quantum annealing.

To achieve this aim, the following objectives are accomplished:

– to integrate quantum annealing in machine learning models with LightGBM;

– to predict learning models with LightGBM utilizing quantum annealing to perform hyperparameter optimization.

4. Materials and methods

The object of this study is the prediction of digital learning achievement. The main hypothesis of the study is the integration of machine learning algorithms with the quantum annealing optimization method can significantly improve the accuracy and efficiency in predicting digital learning models compared to conventional approaches such as grid search and random search. The assumptions underlying this hypothesis include the assumption that the learning data used is representative and has high complexity parameters, thus requiring a more efficient and adaptive optimization method. quantum annealing is expected to be able to explore space solutions more intelligently and quickly, and find optimal configurations in a shorter time. In the context of the complexity of the system complexity described, this study assumes that the digital learning environment has uniform characteristics and that the metric evaluation model used is consistent. This simplification is done to ensure that the focus of the analysis remains on the effectiveness of the prediction method and not on external variables that are difficult to control.

This study involved 500 respondents consisting of active students at the higher education level who participated in brave learning through the learning management system (LMS) platform. Data were collected through two main sources, namely a Likert-based questionnaire that measures cognitive, affective, and motivational aspects, and activity log data from the LMS that includes information such as login frequency, access duration, task completion, and participation in discussion forums. The data structure used includes numeric and categorical variables, with a total of 20 input features classified into three main groups: data demographics, interactive behavior in the LMS, and student perceptions of the effectiveness of digital learning. This data is then processed through the stages of normalization, removal of duplicate data, and handling of missing values before being used in the prediction model training process.

This stage includes data cleaning from duplication and anomalies, handling missing values using the median imputation method and multivariate regression, normalizing numeric features using the min-max scaling technique, and transforming categorical features using one-hot encoding. After the preprocessing process is complete, the data is divided into two parts, namely the training set of 80% and the testing set of 20%, using the stratified sampling method to maintain the proportion of class distribution. Model performance evaluation is carried out using several metrics, including accuracy, precision, recall, F1-score, and AUC-ROC. The evaluation is carried out thoroughly with the 5-fold cross-validation method to avoid overfitting and ensure the model's generalization ability to new data. The integration between LightGBM and quantum annealing in this study is expected to produce a prediction system that is able to accommodate the dynamics of digital learning adaptively and efficiently, as well as support data-based decision-making processes in higher education management in the digital era. This study begins with the design of a system architecture which is further explained in Fig. 1.

Fig. 1 shows the architecture of a machine learning-based learning prediction system with quantum annealing optimization that illustrates a workflow consisting of seven main stages that are integrated with each other to support learning optimization in the digital era. The process starts from the data collection stage, where data is collected through the digital learning assessment form and the institutional database and learning management system (LMS) containing information related to digital learning activities, assessments, and interactions. The collected data is then processed in the data processing stage, which includes cleaning data from duplication and missing values, normalizing numeric scales, transforming categorical features, and exploring the initial data through exploratory data analysis techniques to identify relevant patterns or irregularities before the modeling stage. Then the system performs feature extraction to produce key predictive variables, such as the level of learning engagement, student digital readiness, learning evaluation results, and teaching strategies used. These variables are important inputs in the machine learning model stage, where the light gradient boosting machine algorithm is used as the core model because of its ability to handle large-scale and complex data. At this stage, the parameter space that was optimized is also defined to obtain the most effective model configuration.

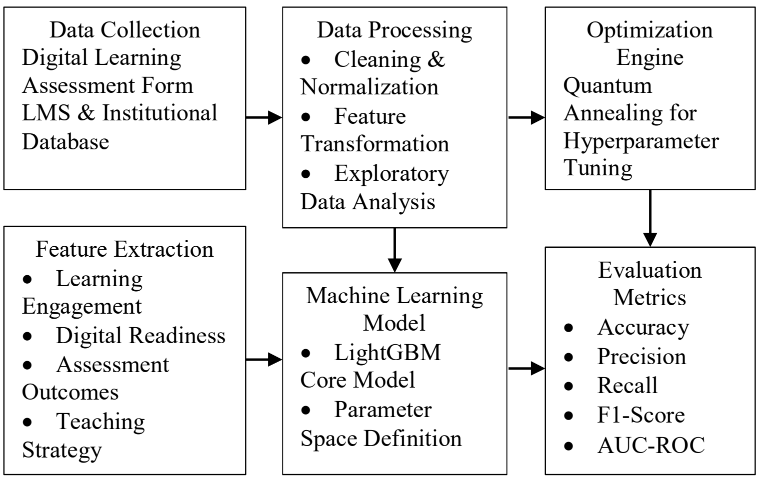

Fig. 1. System architecture

The model optimization process is carried out by the optimization engine which implements the quantum annealing technique to efficiently explore the parameter space and find the global optimum solution, especially for hyperparameters such as the number of decision leaves, tree depth, and learning ratio. The results of the trained model are then evaluated through the evaluation metrics stage, using evaluation indicators such as accuracy, precision, recall, F1-score, and AUC-ROC to measure the performance of learning achievement predictions comprehensively. The integration between the machine learning process and quantum optimization is expected to produce a learning prediction system that is accurate, computationally efficient, and adaptive to the dynamics of digital learning.

5. Quantum annealing results for optimizing learning prediction models in the digital era

5. 1. Integration of quantum annealing in machine learning models with LightGBM

In the development of machine learning-based prediction systems, optimal hyperparameter selection and configuration is one of the main challenges that greatly affect model performance. LightGBM, as a popular and efficient gradient boosting algorithm, is widely used in large-scale classification and regression tasks, including in the context of digital learning model prediction. However, the performance of this model is highly dependent on the combination of hyperparameters such as num_leaves, max_depth, learning_rate, and min_data_in_leaf. A non-optimal combination can cause the model to overfit or underfit, so an intelligent optimization approach is needed to find the best hyperparameter values. In this study, the application of quantum annealing is used to solve this problem efficiently. Mathematically, LightGBM aims to minimize the total loss function which is a combination of the loss function and model complexity regularization contained in (1)

$$\ell_{total} = \sum_{i=1}^{n} \ell\left(y_i, \hat{y}_i\right) + \sum_{t=1}^{T} \Omega\left(f_t\right), \tag{1}$$

where $\ell\left(y_i, \hat{y}_i\right)$ – a loss function such as log loss or mean squared error, and Ω – a complexity penalty to prevent overfitting. The main goal is to find the hyperparameter configuration $h \in H$ which minimizes prediction errors on validation

$$\min_{h \in H} \ell_{val}\left(f_{LBGM}\left(h\right)\right). \tag{2}$$

Search space H *is* very large and not always linear. So, to overcome the complexity and improve search efficiency, a transformation is carried out on this optimization problem into the form of quadratic unconstrained binary optimization so that it can be solved using the quantum annealing method. In the formulation, each hyperparameter value is symbolized in binary form $Z \in \{0,1\}^n$ and the objective function is expressed in (3)

$$\min_{z} z^T Q z, \tag{3}$$

where Q – a symmetric matrix representing the penalty for each parameter combination. The solution of this QUBO system, namely z^*, is then mapped back into the optimal hyperparameter configuration h^* to be used in training the LightGBM model as shown in (4)

$$h^* = decode\left(z^*\right) \rightarrow f_{LGBM}\left(h^*\right). \tag{4}$$

This integration not only improves accuracy, but also training time efficiency because quantum annealing is able to perform probabilistic global searches based on quantum physics phenomena such as tunneling and superposition, which are difficult to imitate by classical optimization algorithms. With quantum annealing the system can avoid local minimal traps in parameter space, which are often the cause of inefficiency of conventional machine learning models. To optimize the 4 hyperparameters of LightGBM will use the values:

h_1: num_leaves → 16 opsi → 4 bit;
h_2: max_depth → 8 opsi → 3 bit;
h_3: learning_rate → 10 opsi → 4 bit.
h_4: min_data_in_leaf → 8 opsi → 3 bit.

Then all hyperparameter combinations can be represented by $n = 14$ binary variables $z1, z2, \ldots, z14$. quantum annealing then solves according to (5)

$$\min_{z1,\ldots,z14 \in \{0,1\}} \sum_{i=1}^{14} \sum_{j=1}^{14} Q_{ijZiZj}. \tag{5}$$

The final result of quantum annealing will provide a Z^* configuration that minimizes the LightGBM loss on the validation data, and this configuration is used for the final training of the model. With this approach, the integration of quantum annealing into the LightGBM model becomes a powerful, intelligent, and computationally efficient hyperparameter optimization method. In the context of this research, the QA use allows the learning model prediction system to be more adaptive to individual learning characteristics and digital data uncertainty, thus encouraging the creation of a more optimal learning process in the digital era

In the process, preprocessing is carried out on the learning dataset which includes features such as learning duration, discussion participation, grade history and number of assignments collected and demographic attributes. The dataset is divided into two parts such as training data of 80% and test data of 20%. The LightGBM model in the process is trained with the default configuration as a baseline. Then the hyperparameter optimization process is carried out using quantum annealing, especially for important parameters such as learning_rate, max_depth, num_leaves, and min_child_samples. This optimization process maps the tuning problem into the form of quadratic unconstrained binary optimization which is then solved using the principle of quantum energy reduction to find the optimal configuration. The results of the training loss and test loss trend graphs are shown in Fig. 2.

In Fig. 2, there was training results such as a training loss trend graph showing that the LightGBM model with default parameters has an initial loss value of 0.49 which decreases slowly to reach 0.33 at the 10^{th} epoch. In contrast, the model optimized with quantum annealing starts training with a lower loss, which is 0.44, and experiences a faster decrease to reach 0.25 at the 10^{th} epoch. This shows that the tuned model not only converges faster but also achieves a lower minimum loss value, indicating effectiveness in learning data patterns during training. In the test loss, the default model shows loss stabilization in the range of 0.34 to 0.35, while the model with quantum annealing is able to maintain the testing loss at a lower number, which is around 0.27 to 0.28. This proves that the optimized model is not only superior in training, but also shows good generalization to new data. In other words, the model does not experience overfitting and is able to provide accurate predictions on data that has never been seen before.

5. 2. Learning model prediction with LightGBM utilizes quantum annealing to perform hyperparameter optimization

The learning model with LightGBM was produce a model that is integrated with the quantum annealing optimization technique in predicting efficient learning models in training and displaying high and stable accuracy performance. Quantum annealing, which is a quantum computing-based approach, is used to optimize LightGBM hyperparameters such as learning_rate, num_leaves, and max_depth, which play an important role in determining the complexity and robustness of the model. This optimization process has successfully improved the predictive ability of LightGBM, as demonstrated by the evaluation of the training and testing accuracy of the model at various epochs. The graph shown in Fig. 2 illustrates the trend of increasing accuracy on both training and testing data during the training process for 10 epochs. At the beginning of training (epoch 1), the training accuracy was recorded at 80%, while the testing accuracy was at 78%. Along with the progress of the training process and the application of the optimal configuration resulting from quantum annealing, the accuracy increased gradually and significantly. At epoch 5, the training accuracy had reached 90% and the testing accuracy was at 88%, indicating that the model not only learned well from the training data, but also able to generalize to new data. Towards the end of training, the model accuracy peaked at 93% for training data and 91% for testing data. The small difference between training and testing accuracy indicates that the model does not experience overfitting, and instead has stability in understanding data patterns. This proves that hyperparameter optimization using quantum annealing successfully balances the learning ability and generalization of the model. The following is an evaluation of the model in Fig. 3.

Fig. 3 will explain the comparison of LightGBM model performance before and after hyperparameter optimization using quantum annealing, based on four main evaluation metrics: accuracy, precision, recall, and F1-score.

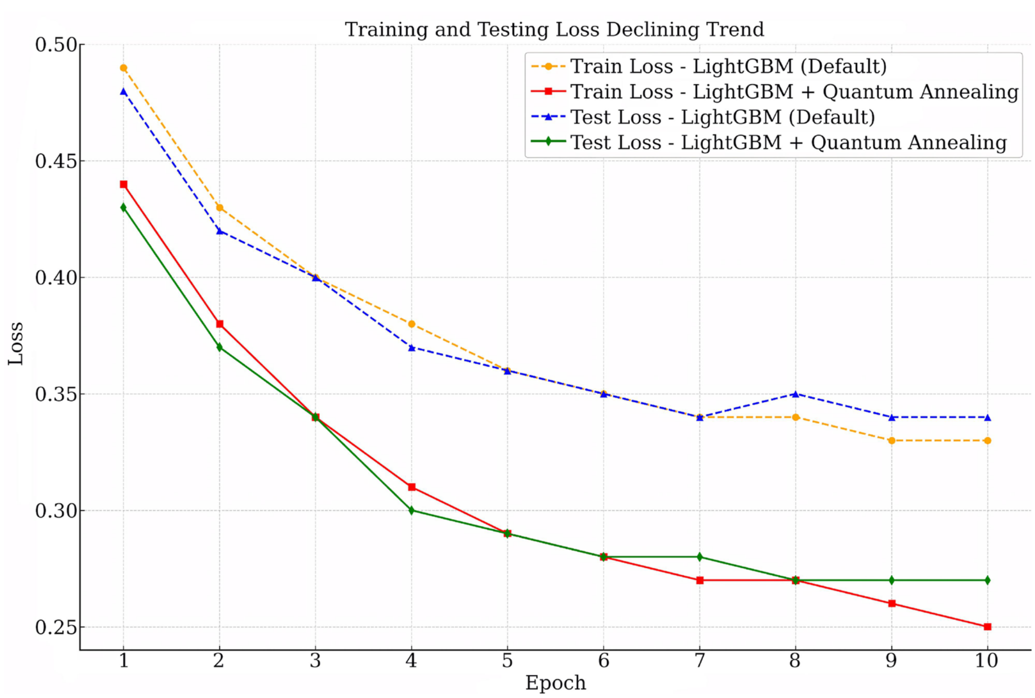

Fig. 2. Training loss and test loss trend graph

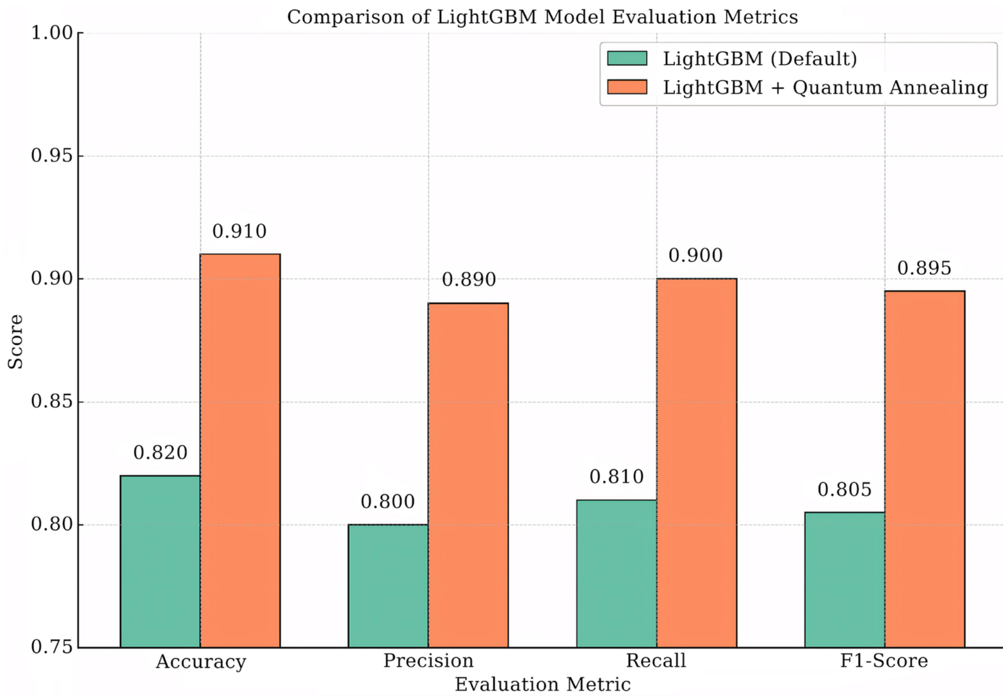

Fig. 3. Model evaluation graph

From the graph, it can be seen that the LightGBM model with default settings has quite good performance, but can still be improved. After optimization with quantum annealing, all four evaluation metrics experienced a significant increase, reflecting an overall improvement in model performance. Model accuracy increased from 82% to 91%, indicating that the tuned model is able to make more accurate predictions overall. Precision, which measures the accuracy of positive predictions, also increased from 80% to 89%, meaning the model is more reliable in producing correct positive predictions. Recall, which measures the model's sensitivity to positive data, increased from 81% to 90%, indicating that the model is better able to detect correct positive cases. F1-score, as a combined metric between precision and recall, increased from 80.5% to 89.5%, reflects that the optimized model is not only more accurate, but also balanced in terms of precision and sensitivity. The improvement in all these evaluation metrics is evidence that quantum annealing is effective in finding the optimal hyperparameter configuration, which ultimately has a direct impact on improving the quality of predictions. This optimized LightGBM model is not only better at classifying, but also more stable and efficient in handling complex learning data. With this performance, the model is very suitable for use in intelligent learning systems that require high accuracy in predicting student achievement or needs.

In the process of building a predictive model, systematic repetition of execution is an important step to ensure the consistency and reliability of the results. The model in the study was run 10 to 30 times to reduce the influence of random fluctuations in the training and testing process. Then validation techniques such as k-fold cross-validation allow the model to be evaluated on various subsets of data in turn, resulting in more stable and representative performance estimates. Evaluation metrics such as accuracy, precision, recall, and F1-score need to be averaged across all validation iterations or folds, and supplemented with dispersion measures such as standard deviation.

6. Discussion of prediction model with quantum annealing for learning model optimization

Model development by performing optimal hyperparameter configuration is very important in the development of machine learning-based prediction systems, especially in the LightGBM algorithm. To overcome the challenge of finding the best combination of hyperparameters, the quantum annealing (QA) approach is used as an efficient and intelligent optimization method. By transforming the problem into the form of quadratic unconstrained binary optimization (QUBO), the search process can be carried out through quantum physics principles such as superposition and tunneling, which enable probabilistic global search. The results obtained in this study significantly demonstrate the effectiveness of the integration of the light gradient boosting machine (LightGBM) algorithm with the quantum annealing optimization method in building an accurate and efficient learning achievement prediction model in the digital era. As shown in Fig. 2, the decreasing trend in loss in both data training and testing shows that the model with hyperparameter tuning through quantum annealing not only reaches convergence faster, but also produces lower loss values than the model with the default configuration. This is explained mathematically in Equations (1) to (5), where the process of finding optimal values for four main parameters – num_leaves, max_depth, learning_rate, and min_data_in_leaf – formulated in the form of quadratic unconstrained binary optimization (QUBO) and solved through a quantum computing approach. The proposed method is unique compared to conventional approaches such as grid search or random search that have been widely used in ML model tuning. quantum annealing utilizes the principles of quantum tunneling and superposition to navigate the solution space globally and probabilistically, thus avoiding the local minima trap that is often an obstacle in conventional ML model optimization.

The comparative results in Fig. 3 confirm this advantage: all evaluation metrics experienced significant improvements after the optimization process, including accuracy increased from 82% to 91%, precision from 80% to 89%, recall from 81% to 90%, and F1-score from 80.5% to 89.5%. This shows that this method comprehensively improves model performance in terms of both precision and generalization ability. When compared to previous studies using Bayesian optimization or simulated annealing, the quantum annealing method is proven to be superior in terms of computational time efficiency and final configuration quality.

Despite the promising results, this study has several limitations. First, access to quantum annealing hardware such as the D-Wave processor is still limited and relies on paid cloud-based services. Second, the transformation of the parameter space into the QUBO binary format requires a complex representation of variables, which if not designed efficiently can affect the scalability of the system. Third, although the model shows stability on the test data, the range of data used is still limited to the context of higher education digital learning, so generalization to other learning domains such as high schools or commercial online courses still needs to be validated.

Unlike Bayesian optimization [14] obtaining an accuracy increase of 5–6% from the LightGBM baseline, which relies on the Gaussian process surrogate model and probability-based exploration, the QA method in this study allows achieving a higher accuracy increase from the baseline from 82% to 91%, as well as improvements in precision metrics from 80% to 89%, recall from 81% to 90%, and F1-score from 80.5% to 89.5% as seen in Fig. 3. This shows that the QA approach not only produces a more optimal parameter configuration but also accelerates model convergence, as seen from the decreasing loss trend in Fig. 2. Then compared to [13] conducting a simulated annealing approach where the gradual temperature decrease process sometimes gets stuck at a local optimum, especially in high-dimensional space, QA offers advantages in terms of computation time and final solution quality because it is able to explore the solution space in a shorter time without losing the quality of the final configuration. In addition, quantum annealing reduces the need for manual tuning that is usually required by grid search.

This study can actually be potentially applied in the context of elementary education, especially to support adaptive learning systems in elementary schools. In an elementary education environment, this model can be used to early identify students who experience learning difficulties, understand their participation patterns in online activities, and provide recommendations for teaching strategies tailored to individual needs. To ensure the effectiveness of using the model at this level, supporting conditions are needed such as the availability of digital learning data through an LMS platform that is appropriate to the age and characteristics of students, teacher involvement in data monitoring, and adequate technological infrastructure in the school environment. With a pedagogically and technically adapted approach, the application of this model in elementary education has the potential to improve the quality of learning interventions and support personalization of education from an early stage.

The weakness of this study lies in the lack of exploration of additional parameters or interactions between features in the dataset that can affect prediction performance. In addition, there has been no sensitivity analysis to determine how much changes in certain hyperparameter values can affect the prediction results. This weakness can be minimized in future studies by conducting ablation tests on parameter combinations or incorporating aspects of model interpretability to explain the contribution of features to prediction results. Further development of this study includes extending the model usage scenario into a real-time recommendation system, where adaptive decisions can be provided directly to students or lecturers based on predicted learning outcomes. Possible challenges include the need for integration with complex LMS systems, model adaptation to sequential or time-based data (e.g. progressive learning), and limitations on the stability of quantum devices when used in production systems. Methodological challenges may also arise in combining quantum optimization with deep learning model architectures that require higher parameterization.

7. Conclusions

1. The integration of quantum annealing (QA) in LightGBM hyperparameter optimization has been proven to be effective in improving the accuracy and efficiency of the training model. By transforming the hyperparameter configuration search problem into quadratic unconstrained binary optimization (QUBO) form, QA is able to explore a large solution space efficiently and avoid local minimum traps. The model results show significant improvements in evaluation metrics such as accuracy of 91%.

2. This study proves that the integration of quantum annealing optimization techniques into the LightGBM model significantly improves the prediction performance of the learning model. By optimizing important hyperparameters such as learning_rate, num_leaves, and max_depth, quantum annealing successfully improves the generalization ability and accuracy of the model. Further evaluation shows significant improvements in all key metrics accuracy increased from 82% to 91%, precision from 80% to 89%, recall from 81% to 90%, and F1-score from 80.5% to 89.5%. This improvement reflects the balance between the detection ability and accuracy of the model in predicting complex data. Repeated testing and the use of cross-validation (k-fold) ensure the consistency of the results, reduce random bias, and increase the reliability of the evaluation.

Conflict of interest

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

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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 current work.

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