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An Efficient Bidirectional Gated Recurrent Unit Approach for Student Study Duration Modeling and Timely Graduation Forecasting

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Abstract
Delays in student graduation remain a persistent challenge in higher education, with approximately 28% of students requiring more than four years to complete their studies, exceeding the standard duration. This study addresses the issue by proposing a predictive model to estimate students' graduation year using a Bidirectional Gated Recurrent Unit (BiGRU) neural network. The model is trained on a combination of academic and financial indicators, including Grade Point (GP) scores from the first to the fifth semester, cumulative Grade Point Average (GPA), and the single tuition fee tier (UKT). The integration of these features allows the model to learn temporal patterns in students' academic progression and financial capacity. Empirical analysis reveals that students in the UKT 8 group consistently demonstrate superior academic performance, as evidenced by their higher average GPA across semesters, compared to students in lower UKT groups. The BiGRU model achieves a Mean Absolute Percentage Error (MAPE) of 9.5%, indicating high predictive accuracy. These findings highlight the potential of deep learning models, particularly BiGRU, in forecasting academic outcomes. Furthermore, the insights generated from this model can serve as a valuable tool for universities in formulating targeted academic interventions and policies aimed at promoting timely graduation and reducing dropout rates.

Keywords : *Forcasting, Bidirectional Gated Recurrent Unit, Mean Absolute Percentage Error, Education*

1 Introduction

On-time Graduation is an important indicator of the success of higher education institutions in supporting students to complete their studies effectively and efficiently [1]. Structured academic progress monitoring is crucial to identify and address obstacles that may lead to graduation delays [2],[3]. In the Bachelor's Degree Program in Informatics at Diponegoro University, the issue of on-time graduation has become one of the main challenges affecting the program's reputation and the institution's accreditation.

This issue is often caused by the lack of an integrated monitoring system to track students' academic progress in real-time [4]. This aligns with the findings of [5],[6], who stated that the lack of centralized access to academic data complicates the process for both academic advisors and students in evaluating their academic achievements. On the other hand, suboptimal communication between students and academic advisors can exacerbate this problem [7]. University should be aware the importance of technology-based academic data management to support proactive interventions.

However, most of the cited studies [2],[3],[4],[5],[6],[7] are derived from contexts outside Indonesia, and the current draft only uses them as summaries. It is important to explore how these

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contexts differ in terms of educational systems, as well as how the graduation prediction models applied abroad compare to those used in this study. In many developed countries, such as the United States, the United Kingdom, and South Korea, academic monitoring systems are often centralized and digitalized, enabling real-time access to student performance data by faculty, advisors, and even students themselves. These systems allow for immediate intervention when performance declines, and they often integrate academic analytics tools to forecast student outcomes. For instance, Kim [2] highlights institutional-level policies in South Korea that utilize early warning systems and academic forecasting tools to guide students toward on-time graduation. Similarly, in the UK and the Middle East, Alshamaila et al. [3] applied deep learning models to predict student performance using real-time course engagement data, prior performance, attendance records, and LMS-based interaction metrics.

In contrast, the academic monitoring system in Indonesia is less integrated. While some universities have begun adopting digital academic systems, many institutions still rely on fragmented or manual record-keeping. Real-time academic monitoring and intervention are not yet fully standardized across Indonesian higher education institutions. This leads to delayed responses in identifying students at risk of delayed graduation and hinders personalized academic guidance. Moreover, communication between students and advisors is often limited to scheduled advisement periods, lacking continuous support mechanisms.

In terms of graduation prediction modeling, international studies generally use a broader range of features, often including behavioral and demographic factors. For example, Kim [2] and Loucif et al. [6] incorporated features such as attendance rates, parental education levels, course withdrawal history, academic engagement, and socio-economic background into their models. These features are typically available through well-maintained institutional databases and reflect a holistic view of the student profile.

Predicting student graduation is one important approach in higher education to improve the quality of academic services and help institutions identify factors that affect student success [8]. By accurately predicting graduation outcomes, universities can implement targeted interventions to support at-risk students and reduce dropout rates. Additionally, this prediction model can help optimize resource allocation, such as academic advising and financial aid, ensuring that students receive the necessary support at critical stages of their studies. Furthermore, it provides valuable insights into curriculum design, enabling institutions to identify areas for improvement and enhance student retention and success. Ultimately, predictive models contribute to fostering an environment where students are more likely to graduate on time and with greater academic achievement.

The prediction of student graduation time has been widely explored using various machine learning techniques, demonstrating their effectiveness in handling structured academic data. Traditional machine learning methods such as the C4.5 decision tree algorithm [1] and Naïve Bayes [8] have been utilized to classify students based on their likelihood of graduating on time. Support Vector Machines (SVM), particularly when optimized with grid search [9], [10] have also shown promise in improving classification accuracy. Furthermore, hybrid approaches [11], such as integrating genetic algorithms with neural networks [10] have been investigated to enhance feature selection and model optimization. These approaches provide interpretable and computationally efficient models but may struggle with sequential dependencies and complex temporal relationships within student performance data.

Deep learning models, particularly recurrent neural networks, have demonstrated superior capabilities in capturing temporal patterns in academic performance prediction. Neural networks could effectively model complex relationships among academic variables. Developed an advanced deep learning model that significantly improved accuracy over traditional methods [12]. The GRU model has gained attention for its efficiency in handling sequential data [13], as shown [14] who proposed a GRU-based grade prediction system with ANOVA-based feature optimization, achieving higher predictive performance. Additionally [15] introduced a bi-directional GRU model (KT-Bi-GRU), which enhanced student performance prediction by integrating knowledge tracing, further improving accuracy. These studies establish Bidirectional GRU as a state-of-the-art approach for graduation prediction, offering advantages in capturing academic progress trends while reducing computational complexity. However, challenges remain in optimizing hyperparameters, improving interpretability, and ensuring practical deployment in real-world educational settings.

2 Research Methods

The dataset used in this study consists of students who have graduated from the Department of Informatics, Diponegoro University, between the years 2014 and 2020. The data includes various academic performance indicators such as semester GPA (IPS1–IPS8), cumulative GPA (IPK), tuition fee group (Gol UKT), and study duration details. This information is utilized to predict the total years required for graduation using an Bidirectional Gated Recurrent Unit (Bi-GRU) model. The overall data processing and prediction workflow is illustrated in Figure 1.

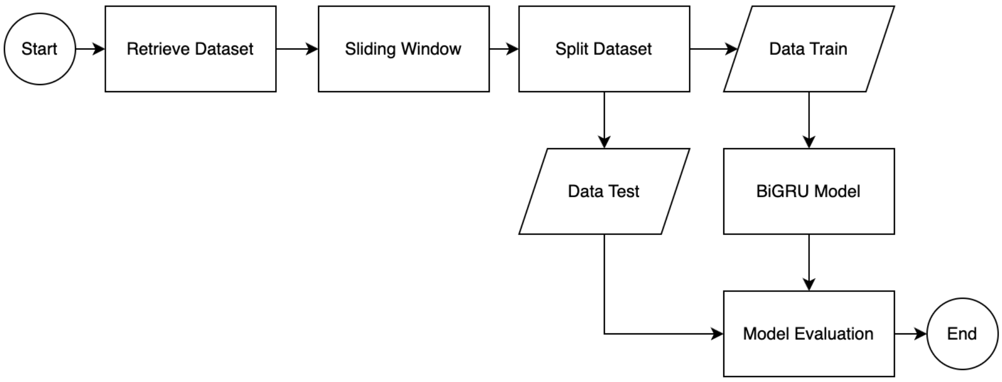

Figure 1. Research methodology framework illustrating the stages for predicting student study periods and on-time graduation.

2.1 Retrieve Dataset

At this stage, the dataset is collected from students who have graduated from the Department of Informatics, Diponegoro University, between 2010 and 2020 with total number of data is 1215. The dataset consists of various academic performance indicators that serve as features for prediction. The key attributes included in the dataset are NIM (Student ID), Nama (Name), Golongan UKT (Tuition Fee Category), Semester GPA (IPS1 - IPS8), Cumulative GPA (IPK), Lama Studi (Study Duration in years), Total Hari (Total Days of Study), Total Bulan (Total Months of Study), Total Tahun (Total Years of Study - Target Variable). The collected dataset undergoes preprocessing, including normalizing numerical data, and encoding categorical data.

2.2 Preprocessing Data

Preprocessing is a crucial stage in preparing the dataset for use in the Bidirectional GRU model. It ensures that the data is clean, consistent, and structured in a way that allows the model to learn effectively. The process begins with handling missing values. The dataset is thoroughly examined for any incomplete or null entries, which can negatively impact model training. For numerical features such as semester GPA (IPS1 to IPS8) and cumulative GPA (IPK), if missing values are minimal, the corresponding records are removed to preserve data quality. However, if missing data is more substantial, statistical imputation methods such as replacing with mean or median values are applied. For categorical features like Golongan UKT (tuition fee category), the most frequent value (mode) is used for imputation if needed.

Following this, feature selection is carried out to retain only attributes that are relevant to the prediction of the target variable, Total Tahun (total years of study). The retained features include semester GPA scores (IPS1 to IPS8), cumulative GPA (IPK), Golongan UKT, and Tahun Lulus (if used for contextual prediction). Irrelevant attributes such as NIM (Student ID) and Nama (Name) are excluded, as they do not contribute to the prediction process and may introduce unnecessary complexity or privacy concerns.

Since deep learning models require numerical input, categorical features must be encoded. The Golongan UKT variable, which is categorical in nature, is converted to numeric form using label encoding, where each UKT category is assigned a unique integer value. This transformation allows the model to process the data without losing the inherent categorical distinctions.

Normalization is then applied to ensure that all numerical features fall within a similar range. Due to the varying scales of attributes for example, GPA scores versus total days of study Min-Max normalization is used to scale all features to a range between 0 and 1. This step is essential to prevent features with larger values from disproportionately influencing the model during training and to improve convergence speed and stability.

Finally, the dataset is split into two subsets: a training set and a testing set. Typically, 80% (972) of the data is allocated for training, while the remaining 20% (243) is used for testing the model's performance. This division allows the Bidirectional GRU model to learn from a large portion of the data while reserving a separate set for unbiased evaluation. The data is split randomly, ensuring that both subsets are representative of the overall data distribution.

2.3 Sliding Window

The sliding window technique is applied to structure the data for time-series forecasting [16][22]. Instead of treating each record independently, the model considers a sequence of past records to predict the target variable (Total Tahun). A window size (n) is defined to determine how many past data points contribute to predicting the next outcome. Each input sample consists of n previous records, allowing the model to learn time-dependent patterns. The sliding window approach transforms the dataset into a 3D shape suitable for deep learning models. This step is crucial because BiGRU models perform better when sequential dependencies in student performance are considered. Illustration sliding window shown in Figure 2.

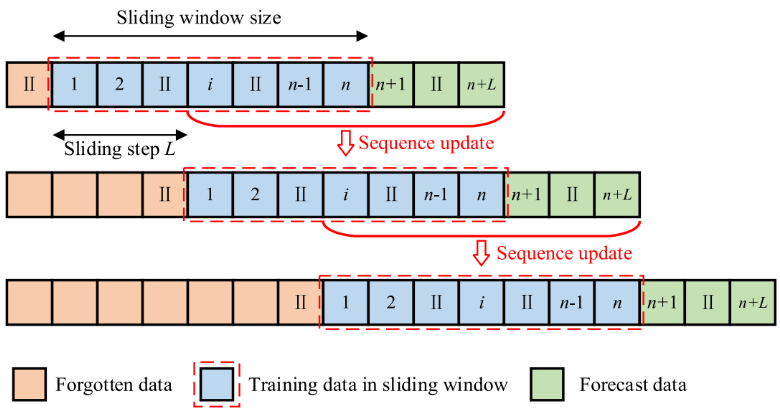

Figure 2. Illustration of recursive prediction based on sliding windows [17]

2.3 Split Dataset

After transforming the dataset using the sliding window technique, the data is split into training and testing sets to evaluate model performance effectively.The dataset is divided into training set (80%) used to train the BiGRU model abd testing set (20%) used to evaluate the model's accuracy. The target variable (Total Graduation Years) is also separated accordingly.

2.4 Bidirectional Gated Recurrent Unit (BiGRU) Model

The given image illustrates Figure 3 and Figure 4 the structure and internal mechanisms of a BiGRU, which enhances sequential learning by processing information in both forward and backward directions [18].

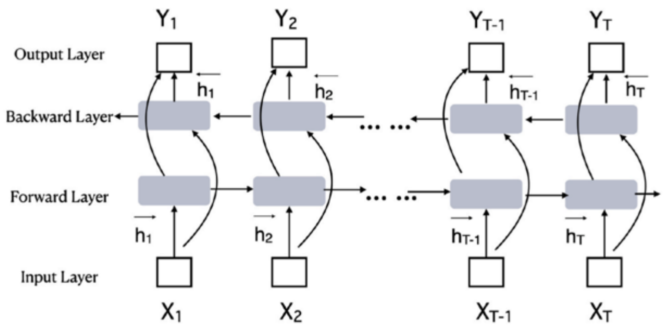

Figure 4. The Bidirectional GRU structure, consisting of an input layer, two recurrent layers processing sequences in forward and backward directions, and an output layer producing the prediction.

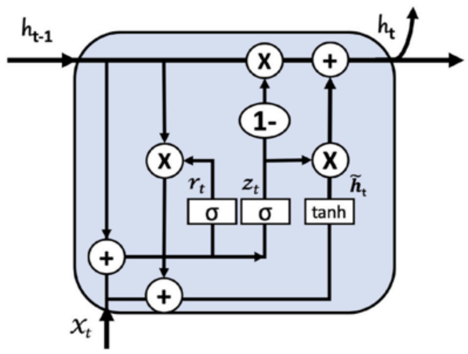

Figure 3. The GRU cell mechanism used in this study, including the reset and update gates, candidate hidden state, and final output computation.

Figure 3 A GRU (Gated Recurrent Unit) cell is a type of recurrent neural network component designed to efficiently capture dependencies in sequential data. It simplifies the traditional RNN architecture by using two main gates the update gate and the reset gate to manage the flow of information. The update gate controls how much of the past information is retained in the current state, helping the model preserve long-term dependencies, while the reset gate determines how much of the previous hidden state to forget when incorporating new input. By combining the current input with the selectively filtered past hidden state, the GRU produces a new hidden state that balances both memory and adaptability. GRUs are known for being computationally lighter than LSTMs while still delivering strong performance in tasks such as language modeling, speech recognition, and time-series forecasting.

Figure 4 This figure illustrates the flow architecture of a Bidirectional Gated Recurrent Unit (BiGRU) network, which is designed to process sequential data by capturing both past and future context. The model consists of an input layer that receives a sequence of data over time, followed by two parallel GRU layers: a forward layer that processes the sequence from beginning to end, and a backward layer that processes it in reverse. Each layer generates a hidden state at each time step based on the input and previous hidden states. These hidden states from both directions are then combined at each time step to form a richer representation, which is passed to the output layer to produce the final results. This dual-directional flow allows the model to understand dependencies in the data more comprehensively, making it highly effective for tasks like language understanding, speech processing, and time-series prediction.

Together, Figure 3 and Figure 4 depict the BiGRU's capability to handle sequential dependencies in data more efficiently than traditional RNNs, making it a powerful tool for graduation time prediction and other time-series forecasting tasks.

2.5 Model Evaluation

Mean Absolute Percentage Error (MAPE) calculates the average absolute difference between the predicted and actual values, expressed as a percentage of the actual values. This metric is particularly useful when you want to understand the size of the errors relative to the magnitude of the true values, making it scale-independent [19]. For example, a MAPE of 10% means that, on average, the predictions are off by 10% from the actual values. One key advantage of MAPE is its interpretability across different datasets and units, which helps in comparing model performance in diverse contexts. However, MAPE can become unstable or misleading when actual values approach zero, as small denominators inflate the percentage error.

Coefficient of Determination (R^2) measures the proportion of variance in the dependent variable that is predictable from the independent variables. It essentially quantifies how well the model captures the underlying trends in the data. An R^2 of 1 indicates perfect prediction with no unexplained variance, while 0 means the model's predictions are no better than simply using the mean of the actual values. Negative values can occur if the model performs worse than the mean prediction. R^2 is widely used to assess the goodness-of-fit of regression models, helping to understand how much of the variability the model accounts for. It complements error metrics by offering a normalized measure of explanatory power [20].

Root Mean Squared Error (RMSE) calculates the square root of the average squared differences between predicted and actual values, penalizing larger errors more heavily than smaller ones due to the squaring operation. This makes RMSE sensitive to outliers or large deviations, which is useful when such errors are particularly undesirable. The units of RMSE match those of the target variable, making it intuitive to understand in the context of the problem. A smaller RMSE value indicates that the model's predictions are, on average, closer to the actual values, and it is often used to compare the overall accuracy of different models [21].

These evaluation metrics provide a thorough and balanced assessment of regression models by addressing multiple facets of prediction quality. MAPE quantifies the relative size of errors as a percentage, offering insight into how predictions deviate proportionally from actual values. The R^2

metric reveals how much of the variance in the target variable is captured by the model, reflecting its overall explanatory power. RMSE places greater emphasis on larger errors by squaring the deviations before averaging, making it useful for understanding a model's sensitivity to significant prediction mistakes. By using this diverse set of metrics, one can gain a comprehensive and nuanced understanding of each model's strengths and weaknesses, ensuring a more informed evaluation beyond any single measure.

3 Results and Discussion

This section presents the performance comparison of four recurrent neural network architectures GRU, LSTM, BiLSTM, and BiGRU evaluated on a regression task using key metrics such as Mean Absolute Percentage Error (MAPE), Coefficient of Determination (R^2), and Root Mean Squared Error (RMSE). Each model was trained using two different configurations of neurons: 64 and 128, to assess the impact of model capacity on prediction quality.

Table 1. Experimental Result

No	Model	Neurons	Learning Rate	Optimizer	MAPE (%)	R^2 Score	RMSE
1	GRU	64	0.01	RMSProp	13.52	0.82	4.12
2	GRU	128	0.001	RMSProp	12.14	0.85	3.78
3	GRU	64	0.001	Adam	14.53	0.85	4.33
4	GRU	128	0.001	Adam	12.44	0.85	4.55
5	LSTM	64	0.01	RMSProp	12.91	0.83	3.95
6	LSTM	128	0.001	RMSProp	11.52	0.91	3.62
7	LSTM	64	0.001	Adam	11.56	0.83	4.64
8	LSTM	128	0.001	Adam	11.77	0.89	4.66
9	BiLSTM	64	0.01	RMSProp	11.22	0.90	3.50
10	BiLSTM	128	0.001	RMSProp	10.11	0.91	3.20
11	BiLSTM	64	0.001	Adam	11.67	0.83	4.33
12	BiLSTM	128	0.001	Adam	11.55	0.84	4.87
13	BiGRU	64	0.01	RMSProp	10.72	0.89	3.35
14	**BiGRU**	**128**	**0.001**	**RMSProp**	**9.51**	**0.93**	**2.95**
15	BiGRU	64	0.001	Adam	11.54	0.84	4.34
16	BiGRU	128	0.001	Adam	11.78	0.89	4.98

The experimental results clearly show that bidirectional neural network models deliver better regression performance than unidirectional models across all important evaluation metrics. Notably, the BiGRU model configured with 128 neurons stood out by achieving the most accurate predictions, as reflected by the lowest Mean Absolute Percentage Error (MAPE) of 9.51%, the highest coefficient of determination (R^2) at 0.93, and the smallest Root Mean Squared Error (RMSE). This superior performance demonstrates the advantage of processing sequence data in both forward and backward directions, allowing the model to leverage information from past and future time steps for a deeper understanding of temporal relationships.

The consistent improvement in performance when increasing the number of neurons from 64 to 128 across all model types highlights the importance of model capacity in capturing complex data patterns. Larger networks provide greater representational power, enabling them to better fit the underlying trends in the data. This trend was observed universally, confirming that expanding network size plays a crucial role in enhancing regression accuracy regardless of the specific architecture employed.

When comparing unidirectional models, the LSTM slightly outperformed the GRU, which may be attributed to its more intricate gating mechanisms that help regulate information flow more effectively. However, despite the simpler design of the GRU, its bidirectional variant managed to achieve comparable or even better accuracy than the BiLSTM. This suggests that the bidirectional GRU strikes a balance between model complexity and performance, benefiting from both efficient structure and the ability to capture temporal dependencies in both directions.

Overall, these findings emphasize that bidirectional architectures, especially BiGRU with sufficient neurons, are highly effective for regression tasks involving sequential data. They not only improve predictive accuracy but also maintain computational efficiency, making them a practical choice for real-world applications requiring robust time-series modeling.

4 Conclusion

This study systematically evaluated the performance of four recurrent neural network architectures GRU, LSTM, BiLSTM, and BiGRU on a regression task, considering two model capacities of 64 and 128 neurons. The evaluation metrics, including Mean Absolute Percentage Error (MAPE), Coefficient of Determination (R^2), and Root Mean Squared Error (RMSE) provided a comprehensive understanding of the models' predictive accuracy and reliability.

The results clearly indicate that bidirectional architectures, BiGRU and BiLSTM, outperform their unidirectional counterparts by effectively leveraging information from both past and future contexts within sequential data. This bidirectional processing enables the models to capture richer temporal dependencies, which translates into more accurate and robust predictions. Among all tested models, the BiGRU with 128 neurons consistently achieved the best performance across all metrics, delivering the lowest error rates and highest explanatory power. This suggests that the BiGRU's simpler gating mechanism, combined with bidirectional context, strikes an optimal balance between model complexity and learning capability. Additionally, increasing the number of neurons from 64 to 128 universally improved model performance, underscoring the importance of sufficient network capacity to model complex data patterns. While LSTM models also showed strong results, their computational overhead compared to GRU and BiGRU may be a consideration depending on resource constraints.

In conclusion, the findings of this study underscore the strong potential and effectiveness of the Bidirectional Gated Recurrent Unit (BiGRU) model, particularly when configured with a higher number of neurons, in addressing regression tasks that involve sequential or time-dependent data. The results suggest that this architecture not only offers robust predictive capabilities but also maintains computational efficiency, making it well-suited for complex temporal modeling. Looking ahead, future research directions may include the incorporation of advanced components such as attention mechanisms or the development of hybrid architectures that combine the strengths of multiple models, with the aim of further improving the model's predictive performance and enhancing its interpretability in real-world applications.

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