Comparison of Indonesia's Open Unemployment Rate Prediction System Using Deep Learning and XGBoost

Minto Waluyo, Rusdi Hidayat Nugroho, and Basuki Rahmat

***Abstract*— Predicting the unemployment rate with precision is essential for policymakers, economists, and business leaders, as it enables effective decision-making in economic planning and resource distribution. This research conducts a comparative evaluation of two prominent machine learning methods—Deep Learning and XGBoost—for forecasting Indonesia's Open Unemployment Rate (OUR). Drawing on data from Indonesia's Central Bureau of Statistics, the study builds and assesses two predictive models: one based on Deep Learning and the other on XGBoost. Model performance is measured using key metrics such as Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Success Percentage. Findings reveal that XGBoost surpasses Deep Learning in accuracy for predicting Indonesia's OUR. Although the Deep Learning model excels at identifying intricate patterns, XGBoost provides superior interpretability throughout training and testing. This analysis underscores the advantages and drawbacks of each method in unemployment forecasting, offering actionable insights for subsequent research and real-world economic prediction tools.**

***Index Terms*—Deep Learning, Open, Prediction, Rate, Unemployment, XGBoost.**

I. Introduction

Open unemployment is often a major issue in the economy, as it can lead to decreased productivity and income among the population, which in turn has the potential to trigger poverty and various other social problems. This issue remains a significant challenge for developing countries, including Indonesia. In Indonesia itself, open unemployment continues to be an important issue that is actively discussed. The impacts of unemployment include a decline in productivity and public income, which may ultimately lead to poverty and various social issues [1]-[4].

According to Central Bureau of Statistics (CBS), unemployment includes individuals who are actively seeking work, those preparing to start a new business, people who are not looking for work because they believe they won't find any, and individuals who have a job but have not yet started working [5]. This broad definition highlights that unemployment isn't limited to those submitting job applications, but also encompasses discouraged workers and future entrepreneurs. It reflects a more inclusive understanding of labor market dynamics.

One of the goals of national development is to improve the welfare of the people. As a developing country, Indonesia needs to implement various changes to support national development. These efforts aim to create national stability, a conducive investment environment, and high economic growth in order to reduce the open unemployment rate. Several factors that influence the level of open unemployment include economic growth, wage levels, inflation, and investment.

The Open Unemployment Rate (OUR) refers to the percentage of the labor force classified as unemployed [5]. A high OUR indicates that a large portion of the workforce has not been absorbed into the job market. Therefore, a system to predict the OUR in Indonesia is needed to identify the number of workers who have not yet secured employment. This enables the government, particularly the Ministry of Manpower, to take anticipatory measures, such as increasing job opportunities and creating employment for the productive workforce.

A high Open Unemployment Rate indicates that a significant portion of the labor force has not been absorbed into the job market. To gain insights into future projections regarding the unabsorbed labor force, a predictive system for the Open Unemployment Rate is necessary. Therefore, this research holds significant contribution for the Government of Indonesia, particularly the Ministry of Manpower. The Open Unemployment Rate prediction system is used to estimate how many members of the labor force have not yet secured employment. Consequently, the government—especially the Ministry of Manpower—can take anticipatory measures by increasing job opportunities and promoting entrepreneurship among the productive workforce.

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II. Related works

Previous studies on the Open Unemployment Rate or its predictions can be summarized as follows: Indonesia's Open Unemployment Rate Forecasting System Based on Deep Learning [5], How Close to Full Employment? Revisiting Europe's Unemployment Challenge [6], Investigating the New Keynesian Phillips Curve in the United States: What Explains the Diminishing Link Between Inflation and Unemployment? [7], Labor Unions: Minimum Wage Standards, Seniority Policies, and Duration of Unemployment [8], An experiment utilizing artificial neural networks for forecasting unemployment rates [9], Semi-supervised multi-target regression for survival analysis in time-to-employment prediction using oblique predictive clustering trees [10], Modeling disability: How artificial intelligence influences unemployment for people with disabilities? An empirical study of linear and nonlinear effects [11], The effects of cash transfers to the unemployed on the labor market: Evidence from South Africa [12], The influence of increased labor market rigidity on employment growth in OECD countries [13], Forecasting one-year employment results after traumatic brain injury: A CENTER-TBI study [14]. Each comparison of previous research findings is presented in Table I.

TABLE I
Comparison with Previous Research

No.	Authors	Research Title	Research methods	Result
1	Basuki Rahmat, Intan Yuniar Purbasari ,Ni Ketut Sari, Widiwurjani, Budi Nugroho, Helmy Widyantara	Indonesia's Open Unemployment Rate Prediction System Using Deep Learning	Using Deep Learning method	The success rate during training is 97.93%, while during testing it is 92.10%.
2	Meryem Gökten, Philipp Heimberger, Andreas Lichtenberger	How far from full employment? The European unemployment problem revisited	Using the Beveridge (full-employment-consistent) rate of unemployment (BECRU) method	This research analyzes deviations from full employment in EU countries from 1970 to 2022 using the Beveridgean full-employment-consistent unemployment rate, highlighting historical trends, the impact of economic crises, and its predictive value for youth unemployment and inactivity.
3	Rouven E. Haschka	Examining the New Keynesian Phillips Curve in the U.S.: Why has the relationship between inflation and unemployment weakened?	Using a comprehensive review methodology to analyze the evolution of the Phillips curve within a New Keynesian framework	This study examines the changing relationship between inflation and unemployment in the U.S. via the Phillips curve within a New Keynesian framework, revealing that globalization and anchored inflation expectations have diminished this link since the 1980s—especially during the Covid-19 pandemic—casting doubt on the Phillips curve's utility for monetary policy.
4	Fernando Alvarez, Robert Shimer, Fabrice Tourre	Unions: Wage floors, seniority rules, and unemployment duration	Using a dynamic equilibrium search model	This research analyzes how unions affect unemployment and wages in a dynamic search model, showing that union-imposed minimum wages and seniority-based job allocation lead to rest unemployment, compressed wage distribution, high job turnover, and lower overall unemployment compared to random job allocation.
5	Cosimo Magazzino, Marco Mele, Mihai Mutascu	An artificial neural network experiment on the prediction of the unemployment rate	Using an Artificial Neural Network (ANN) methodology	This research introduces an advanced Artificial Neural Networks methodology with a Genetic test to accurately forecast unemployment in 23 developed countries (1998–2016), highlighting the significant influence of GDP, labor productivity, population growth, and AI innovation, while inflation and other factors play a lesser role.
6	Viktor Andonovikj, Pavle Boškoski, Sašo Džeroski, Biljana Mileva Boshkoska	Survival analysis as semi-supervised multi-target regression for time-to-employment prediction using oblique predictive clustering trees	Using a semi-supervised oblique predictive clustering tree (OPCT)	This study presents an innovative method employing semi-supervised oblique predictive clustering trees for survival analysis to predict jobseekers' time-to-employment, validating its efficacy on real-world Slovenian data and benchmarking it against six cutting-edge AI techniques.
7	Mehdi Abid, Ousama Ben-Salha, Karim Gasmi, Nasareldeen Hamed Ahmed Alnor	Modelling for disability: How does artificial intelligence affect unemployment among people with disability? An empirical analysis of linear and nonlinear effects	Using two econometric methods: System Generalized Method of Moments (System GMM), and Panel Smooth Transition Regression (PSTR)	This study investigates AI's influence on unemployment among individuals with disabilities in 40 countries (2007–2021), revealing that AI typically lowers unemployment rates, though effects vary by income level and gender, with benefits for women and low-income countries appearing only after surpassing a specific AI adoption threshold.
8	Haroon Bhorat, Timothy	The labour market	Using a staggered ,	Unconditional cash transfers, such as South Africa's Social Relief of

	Köhler	effects of cash transfers to the unemployed: Evidence from South Africa	heterogeneity-robust difference-in-differences (DID) design	Distress grant, temporarily enhance job searching, entrepreneurship, and employment—primarily in wage and informal sectors—but these benefits diminish over time.
9	Rasmus Wiese, João Tovar Jalles, Jakob de Haan	The impact of increasing labour market rigidity on employment growth in OECD countries	Using a novel, narrative-based dataset of labor market reform indicators and applies the local projections method	Labor market counter-reforms, especially those enhancing employment protection for temporary workers, drive employment growth in robust economies, whereas modifications to unemployment benefits show no notable impact.
10	Helena Van Deynse, Wilfried Cools, Viktor-Jan De Deken, Bart Depreitere, Ives Hubloue, Ellen Tisseghem, Koen Putman	One-year employment outcome prediction after traumatic brain injury: A CENTER-TBI study	Using three distinct algorithms: elastic net logistic regression, random forest and gradient boosting.	This study utilized data from the CENTER-TBI cohort (2014–2017) spanning 18 European countries to forecast return-to-work outcomes one year following traumatic brain injury.

Drawing on prior studies outlined in Table I, this paper investigates an alternative method for forecasting the Open Unemployment Rate. Its objective is to compare Deep Learning and XGBoost approaches. The application of Deep Learning for predicting the Open Unemployment Rate was addressed in our previous research [5]. This study incorporates four additional years of more recent data and employs a slightly modified Deep Learning architecture. Meanwhile, the XGBoost method is deliberately included as a comparative approach for predicting the Open Unemployment Rate.

The connections among nodes in a Deep Learning framework mirror those among PCs in a computer network structure [5]. However, a large number of nodes typically increases the complexity and makes continuous analysis more challenging. Both Deep Learning and XGBoost have demonstrated effectiveness in addressing time series prediction tasks. Several examples of Deep Learning applications in time series forecasting are presented in the following papers: [5], [15]-[20]. In the meantime, various examples of XGBoost applications in time series prediction tasks are presented in the following papers: [21]-[26].

III. Proposed Methodology

One approach to measuring unemployment is the Open Unemployment Rate (OUR), defined as the percentage of unemployed individuals relative to the total workforce. The workforce encompasses individuals aged 15 and above who are either currently employed, have secured a job but have not yet begun working, or are unemployed.

Per Central Bureau of Statistics (CBS) data, the Open Unemployment Rate represents the percentage of unemployed individuals relative to the total workforce, as expressed in Equation (1) [5].

$$OUR = \frac{a}{b}\, x\, 100\% \qquad (1)$$

where:

a = Number of unemployed individuals.

b = Number of workforce.

This research aims to predict the Open Unemployment Rate using the Deep Learning and XGBoost methods.

A. Research Data

The role of information and communication technology (ICT) in gathering time-series data on the Open Unemployment Rate—particularly in Indonesia—has been implemented by the Central Bureau of Statistics (CBS). Overall, CBS's services for statistical data collection in Indonesia extend beyond the Open Unemployment Rate, as illustrated in Fig. 1.

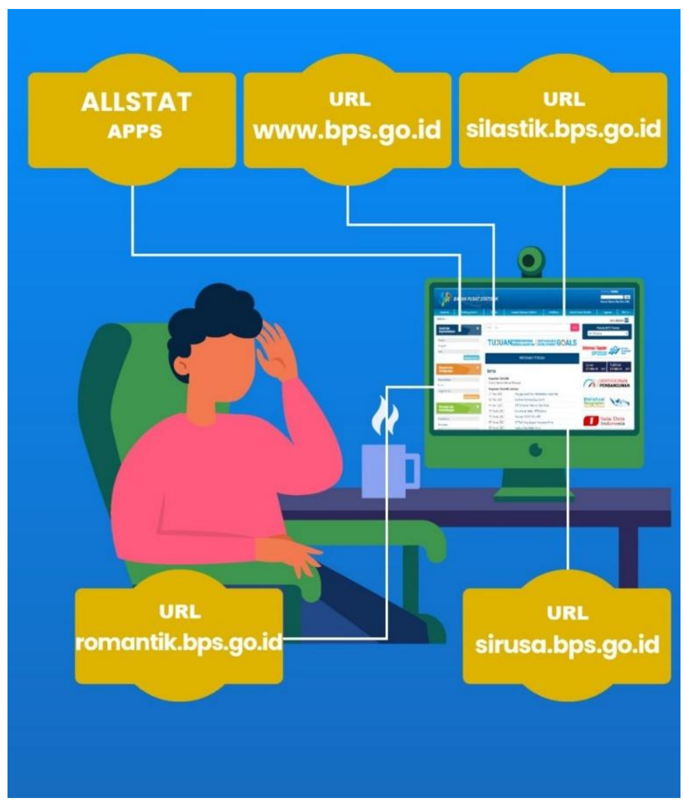

Fig. 1. Some services of the Central Bureau of Statistics (CBS) of Indonesia.

This study utilizes Open Unemployment Rate data for Indonesia spanning 1997 to 2024, with the dataset partitioned as outlined in the Model Structure description.

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B. Model Structure

Utilizing the research data outlined above, a model structure is developed to meet this objective. The dataset is split between the Training Phase and Testing Phase. For training, Open Unemployment Rate data from Indonesia (1997–2016, 20 years) is employed to forecast the rate from 2017–2020 (4 years). For testing, the dataset is advanced by 4 years, using data from 2000–2020 (20 years) to predict the rate from 2021–2024 (4 years).

Consequently, the prediction system is structured to use the preceding 20 years of data to forecast the Open Unemployment Rate for the subsequent four years. Accordingly, the configuration of the Training Data and Testing Data according to this design is illustrated in Fig. 2.

Subsequently, grouping the Open Unemployment Rate data every two years from 1997 to 2016 yields ten input groups. Likewise, the four-year predicted Open Unemployment Rate data is organized into two output groups. This configuration serves as the system model—a structure with ten inputs and two outputs—for the Deep Learning and XGBoost architectures.

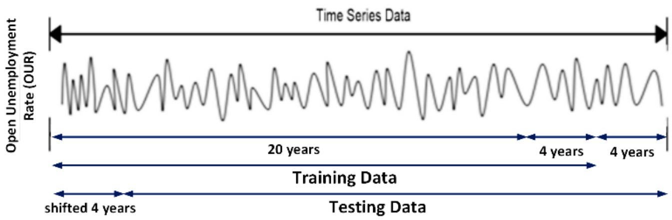

Fig. 2. Data model structure setup.

C. Deep Learning and XGBoost Architecture

Based on the model structure described above, the Deep Learning and XGBoost systems are designed with ten inputs and two outputs.

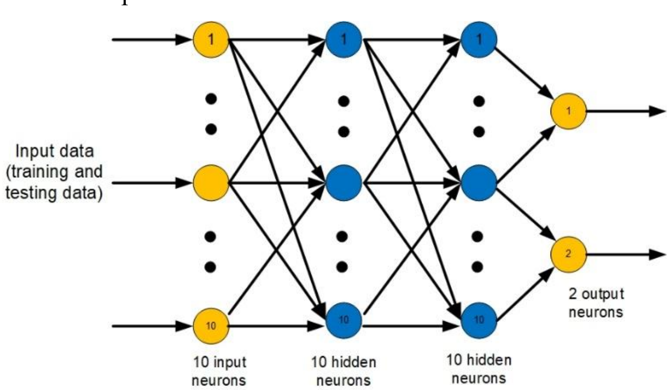

Fig. 3. Deep Learning Architecture.

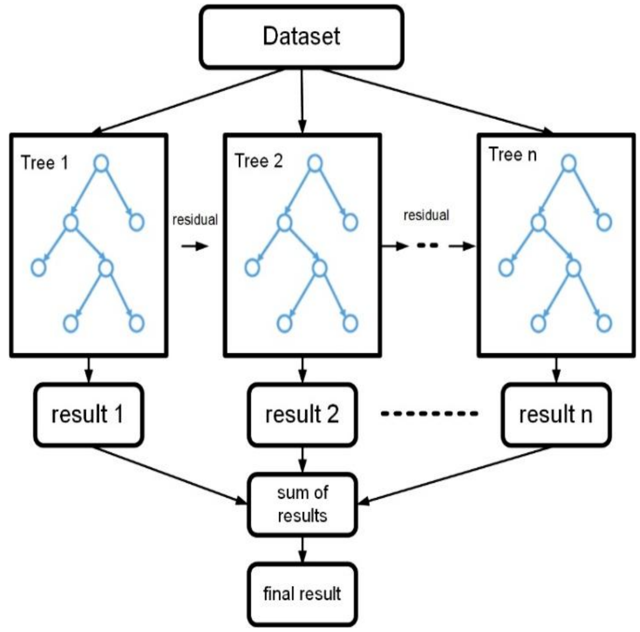

Fig. 4. XGBoost Architecture.

As illustrated in Fig. 3, the nodes are colored blue and yellow. The blue nodes in the hidden layers employ the ReLU activation function, whereas the yellow nodes in the input and output layers utilize the ReLU and Sigmoid activation functions, respectively.

Fig. 4 shows the XGBoost architecture. XGBoost is a supervised learning algorithm that uses a boosting technique to produce more accurate predictive models. In the process, a model trained on labeled data is used to predict new data that has not been previously analyzed. Boosting itself is an ensemble learning approach that builds a series of models sequentially, where each subsequent model aims to correct the weaknesses of the previous one. XGBoost falls into the category of core tree boosting algorithms that follow this principle. In addition, XGBoost extends the generalized gradient boosting method by adding a regularization element. This addition aims to reduce the risk of overfitting and supports the use of various types of loss functions that have differentiable derivatives. These features make XGBoost more reliable and superior in enhancing model performance.

D. Training and Testing Flowchart

Using the Deep Learning network architecture depicted in Fig. 3, the training and testing processes for Deep Learning are structured as shown in Fig. 5.

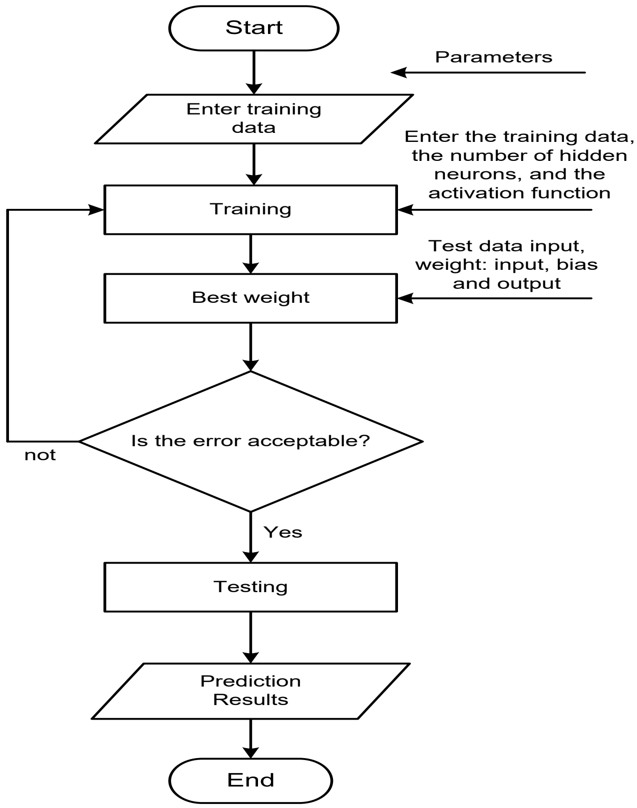

Fig. 5. Flowchart of the training and testing process for Deep Learning.

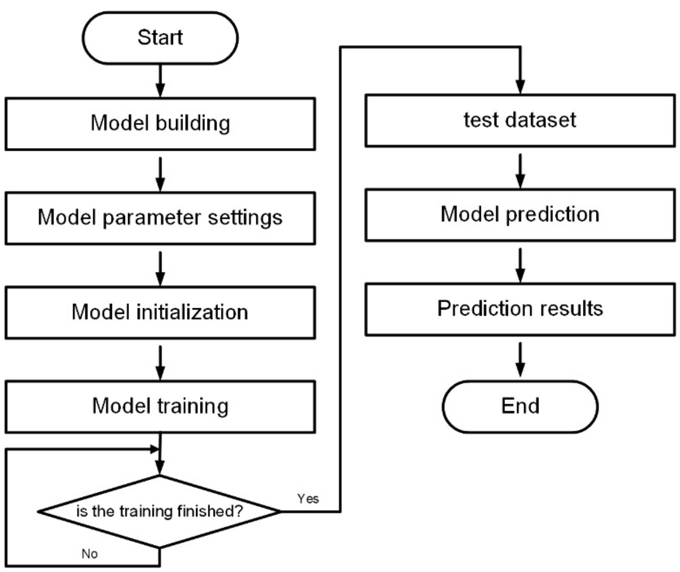

Fig. 6. Flowchart of the training and testing process for XGBoost.

According to Fig. 5, the Deep Learning network is trained with input-output pairs from the training data model. During training, weights and biases are optimized using suitable activation functions. The network's output is compared to the target output until the error falls within an acceptable threshold. The optimal weights are then applied in the testing phase, where new data is fed through each layer to generate a prediction—the Open Unemployment Rate in this study.

Likewise, as depicted in Fig. 6, the XGBoost network follows a comparable training and testing workflow. The training phase involves multiple steps: constructing the XGBoost model, configuring its parameters, initializing the model, and performing the training. Once training is complete, testing proceeds by inputting new data. The XGBoost model then generates predictions, yielding the network's output—the Open Unemployment Rate in this study.

The performance evaluation outcomes for each prediction method are presented as Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Success Percentage (%).

IV. Results and Discussion

The Deep Learning network was trained with 10 inputs and 2 outputs using Open Unemployment Rate data. The training dataset comprises Indonesia's Open Unemployment Rate from 1997 to 2016 (20 years), employed to forecast the rate from 2017 to 2020 (4 years). Data points are processed via a two-year interval structure. The outcomes of the training process, conducted over 500 epochs, are presented in Fig. 7, Fig. 8, and Fig. 9.

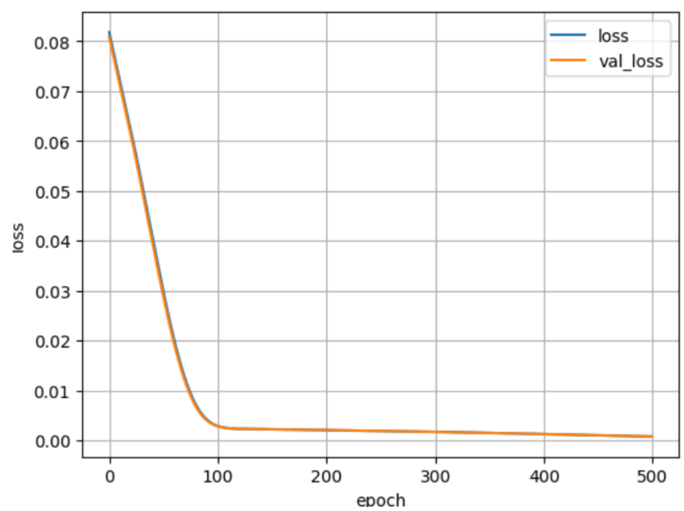

Fig. 7. The process of reducing the loss in the mean squared error in the Deep Learning training process.

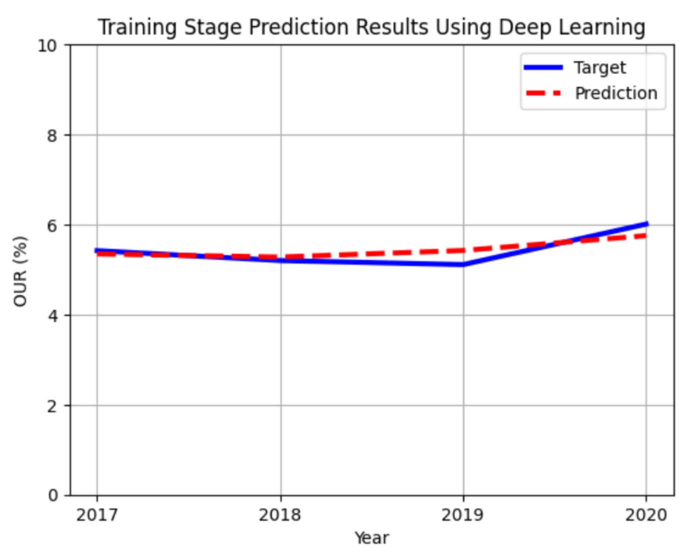

Fig. 8. The output of the Deep Learning training process.

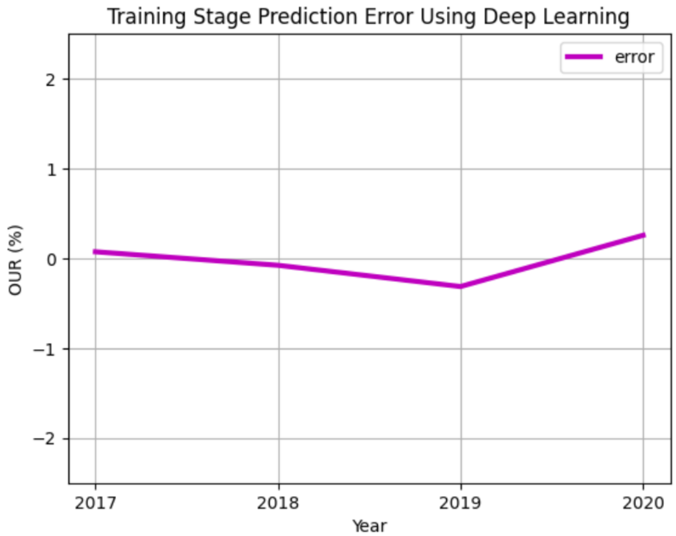

Fig. 9. The error prediction of the Deep Learning training process.

Using the same training data, the training process for XGBoost was carried out. The results are shown in Fig. 10 and Fig. 11.

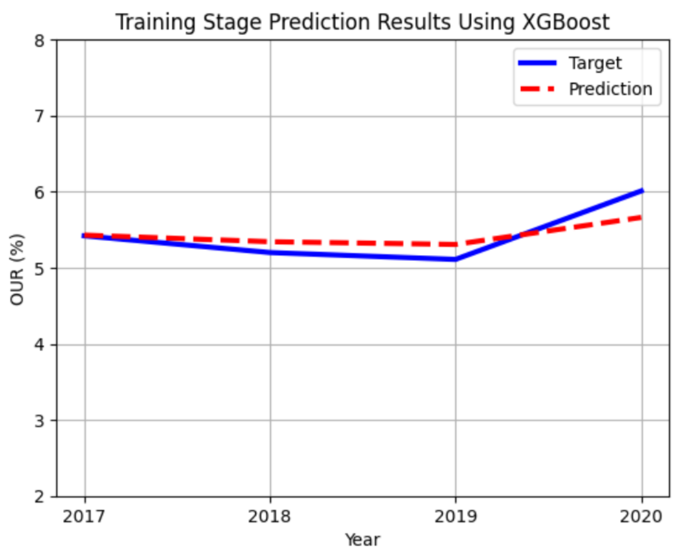

Fig. 10. The output of the XGBoost training process.

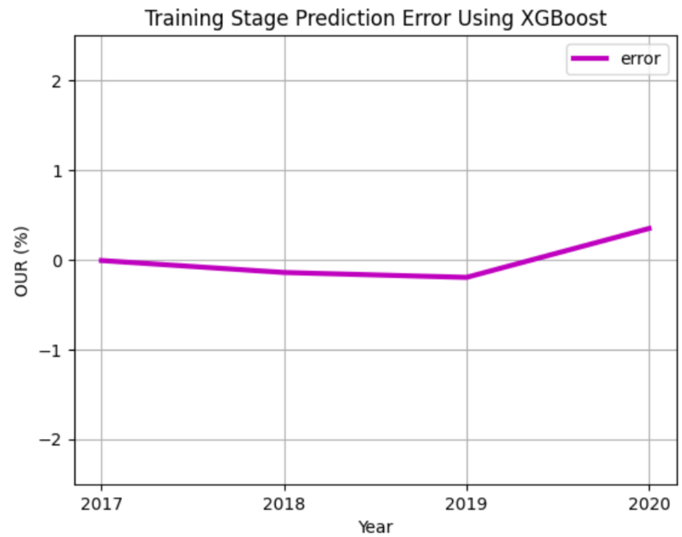

Fig. 11. The error prediction of the XGBoost training process.

The training results of Deep Learning and XGBoost for the Open Unemployment Rate prediction system are briefly presented in table form, as shown in Table II.

TABLE II
RESULTS OF THE TRAINING PROCESS

Method	Iteration/ maxdepth	MSE	RMSE	MAPE	Success Percentage (%)
Deep Learning	500	0.043927	0.209588	3.31	96.69
XGBoost	10	0.045108	0.212387	3.14	96.86

From the training results in Table II, it can be seen that XGBoost delivers better performance than Deep Learning in predicting the Open Unemployment Rate, as indicated by a slightly higher success percentage. Although the difference is minimal, Deep Learning required 500 iterations to achieve its performance. In contrast, XGBoost was configured with a tree depth of 10. Deeper trees can better model complex feature interactions, but if too deep, they may lead to overfitting. Additionally, larger trees require more time for the training process.

In the testing phase, Indonesia's Open Unemployment Rate data from 2000 to 2020 (20 years) was utilized to forecast the rate from 2021 to 2024 (4 years). The testing results for Open Unemployment Rate predictions using Deep Learning and XGBoost are displayed in Fig. 12 through Fig. 15.

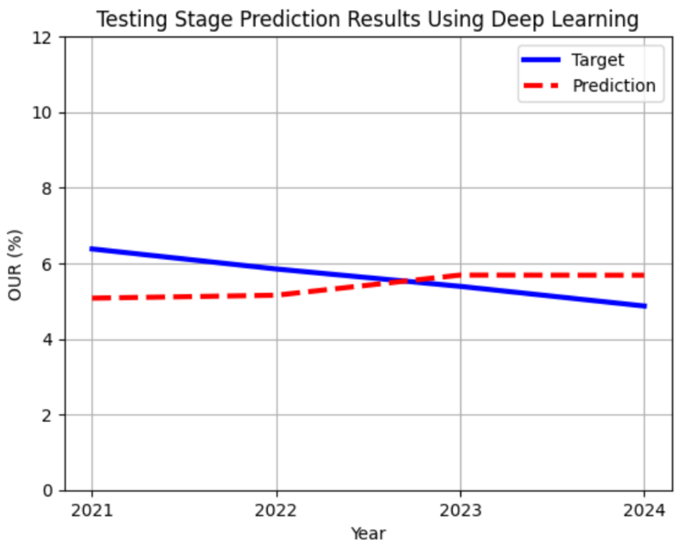

Fig. 12. The output of Deep Learning testing process.

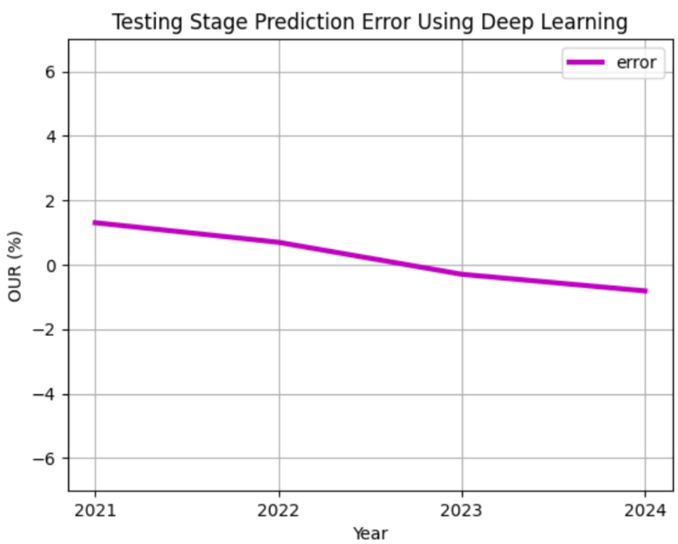

Fig. 13. The error prediction of Deep Learning testing process.

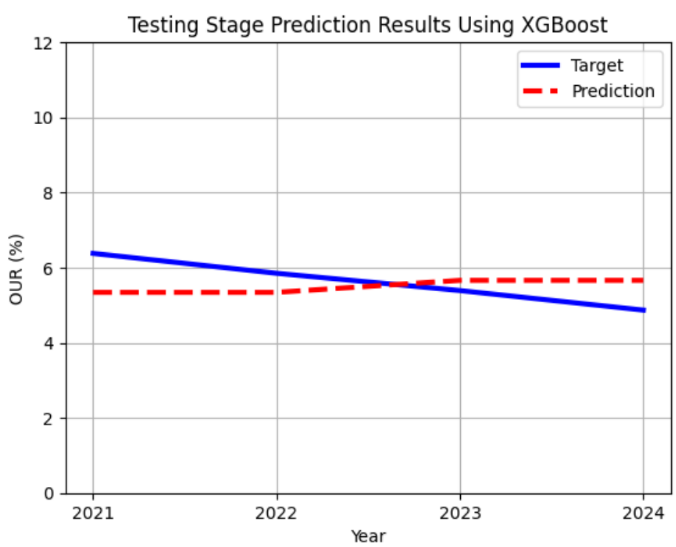

Fig. 14. The output of XGBoost testing process.

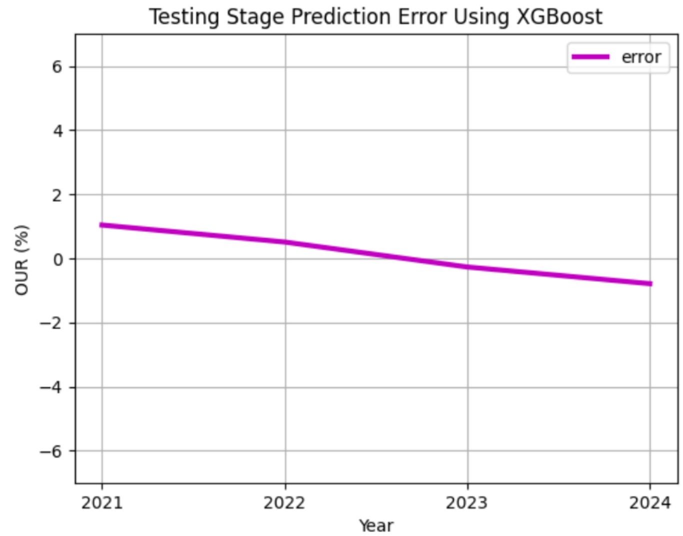

Fig. 15. The error prediction of XGBoost testing process.

The testing results of Deep Learning and XGBoost for the Open Unemployment Rate prediction system are briefly presented in table form, as shown in Table III.

TABLE III
RESULTS OF THE TESTING PROCESS

Method	MSE	RMSE	MAPE	Success Percentage (%)
Deep Learning	0.732861	0.856073	13.64	86.36
XGBoost	0.508745	0.713264	11.56	88.44

V. CONCLUSION

This paper demonstrates that XGBoost delivers slightly better performance than Deep Learning in predicting the Open Unemployment Rate, as indicated by the success percentage. Overall, both the training and testing phases provide a basis for comprehensive performance evaluation. During the training phase, XGBoost outperformed Deep Learning by a margin of 0.17 percent. In the testing phase, XGBoost also showed superior performance, with a margin of 2.08 percent. Therefore, this study concludes that XGBoost consistently outperforms Deep Learning in both the training and testing stages for the case of Open Unemployment Rate prediction.

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