The Role of Advanced Artificial Intelligence in Predicting Indonesia's Economic Growth and Strengthening Economic Decision

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Abstrak. Penelitian ini bertujuan untuk mengembangkan model berbasis kecerdasan buatan dalam menganalisis dan mensimulasikan pertumbuhan ekonomi Indonesia menggunakan berbagai indikator makroekonomi. Penelitian ini mengombinasikan pendekatan machine learning dan deep learning, yaitu Support Vector Regression (SVR), Linear Ridge Regression (LRR), CNN-LSTM, dan CNN-GRU, yang diintegrasikan melalui teknik ensemble. Penelitian menggunakan data makroekonomi bulanan periode 1997–2023. Data yang terkumpul kemudian dibagi menjadi dua data set pelatihan dan pengujian. Kinerja model dievaluasi menggunakan *Root Mean Square Error (RMSE)* untuk mengukur tingkat akurasi prediksi. Hasil penelitian menunjukkan bahwa model berbasis kecerdasan buatan mampu menangkap hubungan yang kompleks dan nonlinier antara variabel makroekonomi dan Produk Domestik Bruto (PDB) Indonesia, termasuk pada periode krisis dan pemulihan ekonomi. Di antara berbagai pendekatan yang diuji, metode *stacking ensemble* menunjukkan tingkat akurasi tertinggi dengan nilai RMSE sebesar 9,83, serta memiliki kesesuaian yang tinggi dengan tren PDB aktual. Temuan ini menunjukkan bahwa kecerdasan buatan dapat menjadi kerangka analisis yang andal dalam memahami dinamika ekonomi dan mendukung pengambilan kebijakan berbasis bukti. Penelitian ini berkontribusi dalam pengembangan alat analisis ekonomi berbasis data yang dapat meningkatkan kualitas perencanaan strategis dan perumusan kebijakan di tengah kondisi ekonomi yang penuh ketidakpastian.

Kata kunci: Keserdasan Buatan; Sistem Pembelajaran Mendalam; Peramalan PDB; Kebijakan Ekonomi; Indikator Ekonomi.

Abstract. *This study aims to develop an artificial intelligence–based model for analyzing and simulating Indonesia's economic growth using macroeconomic indicators. The research employs a combination of machine learning and deep learning approaches, including Support Vector Regression (SVR), Linear Ridge Regression (LRR), CNN-LSTM, and CNN-GRU, integrated through ensemble techniques. Monthly macroeconomic data from 1997 to 2023 were collected and divided into training and testing datasets. Model performance was evaluated using Root Mean Square Error (RMSE) to assess prediction accuracy. The results indicate that AI-based models are capable of capturing complex and nonlinear relationships among macroeconomic variables and Indonesia's Gross Domestic Product (GDP), including during periods of economic crisis and recovery. Among the tested approaches, the stacking* *ensemble method achieved the highest accuracy, with an RMSE of 9.83, demonstrating strong alignment with actual GDP trends. These findings suggest that artificial intelligence provides a reliable analytical framework for understanding economic dynamics and supporting evidence-based policymaking. This study contributes to the development of data-driven economic analysis tools that enhance strategic planning and policy formulation in uncertain economic environments.*

Keywords: *Artificial Intelligence; Deep Learning; GDP Forecasting; Economic Policy; Macroeconomic Indicators*

1. Introduction

The economic condition of a nation is a vital aspect that can represent the well-being of its citizens. One of the primary metrics reflecting economic status is the national Gross Domestic Product (GDP). The GDP measures a country's economic activity; higher GDP values indicate more robust economic activity and, consequently, a potentially higher standard of living for its citizens [1]. A country's GDP is also a benchmark for observing the condition of a country's economic growth. When economic growth is good, it indicates stable economic strength; conversely, a low GDP value indicates instability in a country's economic condition (Ministry of National Development Planning/Bappenas, 2023). In its implementation, GDP is a crucial metric on which governments base their policy-making decisions, as it offers numerous benefits [2]. Governments use GDP data to plan and evaluate economic policies, making informed decisions about fiscal measures like government spending, taxation, and monetary policies, including interest rate adjustments. Moreover, GDP is employed to gauge an economy's productivity by comparing it with production inputs such as labor and capital, which helps determine resource utilization efficiency in producing goods and services.

GDP data also plays a pivotal role in assessing a country's investment appeal. Investors and international financial institutions consider a solid GDP to indicate stability and foreign investment attractiveness [3]. Beyond investment, GDP figures are instrumental in international trade negotiations and in forming economic agreements. Additionally, GDP is a benchmark for setting economic growth targets, with governments and international organizations frequently using these targets in their long-term development plans. Overall, GDP is an invaluable tool for various stakeholders to measure and comprehend the dynamics of a country's economy. Despite its limitations, such as not reflecting income distribution or overall social welfare, GDP remains a fundamental indicator in economic analysis [4]. Several factors determine a country's rise or fall in GDP [5]. First, the price of gold, often viewed as a market confidence indicator, reflects economic uncertainty or risk. Rising gold prices can boost GDP in gold-producing countries through increased exports, while gold-importing countries might see higher production costs and inflation. Second, the price of crude oil, both Brent and WTI, significantly impacts GDP, particularly for countries that import or export oil. High oil prices may increase production and transportation costs, potentially reducing consumption and investment; however, they can enhance national income and support economic growth in oil-exporting countries [6].

Third, the USD/IDR exchange rate impacts Indonesian exports' competitiveness and import costs. A depreciating Rupiah can increase export competitiveness but may lead to higher import costs and inflation, while an appreciating Rupiah generally lowers import costs but could hinder export competitiveness. Additionally, the Indonesia Composite Index (IHSG) is a barometer of the stock market's performance and is often linked with investor confidence; a rising IHSG typically boosts investment and consumption, thereby driving GDP growth [5]. Lastly, M2, a measure of money supply, including cash, savings, and time deposits, reflects monetary policy. An increase in M2 suggests a looser monetary policy that can spur economic growth by enhancing credit availability and boosting consumption and investment. However, if M2 expands too quickly, it risks causing inflation. Inflation is the sixth factor affecting a country's GDP [7]. The inflation rate reflects the price increase of goods and services over time. Moderate inflation is usually associated with healthy economic growth. However, too high inflation can reduce public purchasing power and harm investment, while too low inflation or deflation can signal weak demand and a stagnant economy. The seventh factor is exports and imports, significant components in GDP calculation [1]. Increased exports directly contribute to GDP growth by boosting aggregate demand.

Conversely, imports reflect the consumption of goods and services from abroad. A positive trade balance, the surplus between exports and imports, can promote economic growth. Another critical factor is the bank's benchmark interest rate [4]. The Bank Indonesia Interest Rate (BI Rate) significantly influences borrowing and saving costs. Lowering these rates can stimulate investment and consumption by making borrowing costs more affordable than at previous levels. On the other hand, increasing interest rates tends to suppress investment and consumption due to rising borrowing costs. The ninth factor, household consumption expenditure, is the most significant component of GDP. An increase in consumer spending signifies public purchasing power and robust aggregate demand, both of which can propel economic growth. Conversely, a decline in consumer spending often signals economic difficulties and can dampen GDP growth. The final factor is gross fixed capital formation, reflecting investments in fixed assets such as factories, machinery, and infrastructure. Heightened investment levels suggest business optimism regarding economic prospects and an expansion in production capacity, which can spur long-term GDP growth [8].

The above variables comprehensively play essential roles in accurately predicting GDP growth. The gold price reflects global economic uncertainty and can influence investment decisions, while crude oil prices affect production and transportation costs, which impact goods prices and inflation. The USD/IDR exchange rate influences export and import competitiveness and macroeconomic stability. The Jakarta Composite Index (IHSG) reflects corporate sector performance and capital market conditions, which affect investment and economic growth. The money supply indicates liquidity in the economy, which can trigger inflation or growth depending on the economic situation. Controlled inflation promotes economic growth, while high inflation can hinder consumption and investment. Exports and imports directly affect the trade balance, with exports increasing national income and imports fulfilling raw material and technology needs. The BI Rate is an indicator of monetary policy that influences loan interest rates, investment, and consumption. Household consumption expenditure significantly contributes to GDP, reflecting people's purchasing power [9]. Finally, gross fixed capital formation reflects investment in infrastructure and fixed assets, which boosts long-term production capacity. These variables are interconnected and contribute significantly to projecting a country's economic growth dynamics, including Indonesia's GDP.

Overall, these factors are interrelated and influence GDP growth through various channels. For example, high oil prices can increase inflation and suppress consumption, while loose monetary policy can encourage investment and consumption [3]. A deep understanding of these linkages is crucial for policymakers to formulate effective economic strategies. Meanwhile, the government is responsible for ensuring national economic stability and meeting citizens' needs. Hence, economic and social policies are expected to be precise and of high quality to bring prosperity to the community. GDP trends are invaluable for governments, aiding in informed economic policy formulation [10]. Governments can proactively address economic and social challenges by analyzing these trends, influenced by various factors (Alam et al., 2023). Accurate GDP predictions are crucial for effective policy-making. Organizations like the OECD and IMF use scenario analysis to project long-term GDP trends, essential for developing sustainable strategies, as demonstrated in the IMF's World Economic Outlook report [11].

Research shows that macroeconomic indicators such as unemployment, inflation, and industrial production strongly correlate with GDP growth, providing a predictive base for tailored economic policies [4]. Additionally, studies focused on developing countries emphasize the critical role of GDP forecasts in policy formulation. Accurate projections, influenced by factors like FDI, foreign aid, and trade policies, enable efficient resource allocation and support growth [8]. These findings are invaluable for governments balancing economic growth with price stability. Research on GDP predictions is crucial in shaping responsive and effective economic policies, as highlighted by Huang et al., 2023. In monetary and fiscal policies, cautiousness is paramount, especially before the resolution of a financial crisis, to avoid overly aggressive measures that could exacerbate economic conditions [12]. Accurate forecasts enable governments to anticipate economic shifts, strategically plan interventions, and foster long-term growth. The precision of these projections significantly bolsters strategic capabilities, making the robustness of the data and models critical for effective policy-making [13].

Today's technological era, machine learning and artificial intelligence have become essential tools in enhancing data analysis and projection processes, particularly in complex economic systems. Maliar et al. demonstrated that dynamic economic models can be effectively reformulated using deep learning approaches as nonlinear regression equations, enabling more accurate and flexible economic simulations [3]. Similar findings by Valaitis et al. (2024), Bluwstein et al. (2023), and Atashbar et al. (2023) further highlight the adaptability and effectiveness of machine learning and deep learning in addressing sophisticated financial and macroeconomic challenges across various economic contexts. The automation of data analysis not only improves efficiency but also reduces human error, thereby providing a more reliable foundation for economic decision-making.

These technological advances play a crucial role in improving the quality of Gross Domestic Product (GDP) projection analysis, which is fundamental for strategic planning, crisis management, and resource optimization. Accurate economic forecasts enable governments to formulate effective fiscal and monetary policies, regulate expenditures and revenues more efficiently, and respond swiftly to economic shocks, such as financial crises or inflationary pressures [2]. Moreover, reliable projections support optimal resource allocation by directing investments toward sectors with the highest growth potential, thereby fostering sustainable economic development.

In this context, this research develops a comprehensive simulation model for projecting Indonesia's GDP using key macroeconomic indicators, including gold prices, crude oil Brent and WTI prices, USD–IDR exchange rates, Indonesia Composite Index, money supply (M2) from Indonesia, Japan, the United States, the European Union, and the United Kingdom, inflation rates, exports and imports, Bank Indonesia policy rates, consumption expenditures, and gross fixed capital formation. The proposed model integrates machine learning and deep learning approaches, namely Linear Ridge Regression, Support Vector Regression, CNN-LSTM, and CNN-GRU, to enhance projection accuracy. Furthermore, ensemble learning techniques are employed to combine individual model outputs, allowing the system to leverage the strengths of each method and improve overall predictive performance.

Despite significant advancements in AI-based economic modeling, previous studies on GDP forecasting and macroeconomic analysis have predominantly focused on single-model approaches or short-term predictions using conventional statistical techniques or limited machine learning frameworks. Many existing studies emphasize prediction accuracy without sufficiently addressing the interpretability of relationships among macroeconomic variables or their relevance for policy evaluation, particularly in developing economies. In addition, most prior research has not comprehensively examined model performance across multiple economic cycles, including periods of financial crisis and recovery, which limits the robustness and practical applicability of their findings.

To address these gaps, this study integrates machine learning, deep learning, and ensemble methods using long-term macroeconomic data that encompass various economic conditions in Indonesia. The main contributions of this research are threefold. First, it provides a comprehensive analysis of nonlinear relationships between macroeconomic variables and GDP using artificial intelligence techniques. Second, it evaluates model robustness across both crisis and non-crisis periods, ensuring reliability under volatile economic conditions. Third, it proposes an AI-based simulation framework that supports evidence-based policymaking and long-term strategic economic planning. Through these contributions, this study strengthens the role of artificial intelligence as a practical and reliable tool for enhancing economic analysis and policy formulation in developing countries.

2. Data and Methodology

This section will discuss the data utilized in this research to predict Indonesia's Gross Domestic Product (GDP). It outlines the methodologies applied to analyze and simulate economic trends based on a dataset spanning from January 1997 to December 2023, which includes 17 critical economic indicators. The analysis employs Machine Learning (ML) and Deep Learning (DL) techniques, integrating various predictive models to enhance forecast accuracy and support robust policy-making.

2.1 Data set

This research utilizes a comprehensive dataset comprising 17 vital macroeconomic variables ranging from January 1997 to December 2023, collected monthly. These variables are essential for modeling the GDP of Indonesia and are categorized into the following groups to reflect different economic dimensions:

a) Global Commodity Prices: Includes daily Gold Prices and Crude Oil Brent and WTI Prices, which converted monthly data, assessing the impact of global commodity fluctuations on Indonesia's economy.
b) Foreign Exchange and Market Indices: This consists of daily data for the Exchange Rate (USD to IDR) and the Indonesia Composite Index, converted to monthly values to provide insights into foreign economic interactions and domestic market trends.
c) Monetary Aggregates: Comprises monthly M2 measurements from Indonesia, Japan, the United States, the European Union, and the United Kingdom, sourced from the respective central banks, which reflects the liquidity in the economy.
d) Trade Variables: Includes monthly export and import data for Indonesia, which is crucial for understanding the trade balance and its effect on economic growth, collected from the Bank Indonesia website.
e) Interest and Policy Rates: Features the BI Fund Rate, which influences lending rates and economic expansion, with data gathered monthly from the Bank Indonesia website.
f) Economic Activity Indicators: Involves quarterly data on Consumption Expenditures and Gross Fixed Capital Formation from the Bank Indonesia website, converted to monthly figures using linear interpolation.
g) Inflation Indicators: Captures the Inflation Rate, affecting consumer purchasing power and economic stability, with monthly data collected from the Bank Indonesia website.

Utilizing monthly data across all variables is crucial for capturing the short-term fluctuations and trends within the Indonesian economy. This granularity enables more precise modeling of economic dynamics and provides a nuanced understanding of the impacts of policy changes and external events on GDP.

2.2 Methodology

This section outlines the structured methodology employed in this research to analyze and predict economic trends using advanced machine learning techniques. The process is systematically divided into several key stages, each designed to refine the data and enhance the accuracy of our predictions, as illustrated in the accompanying diagram.

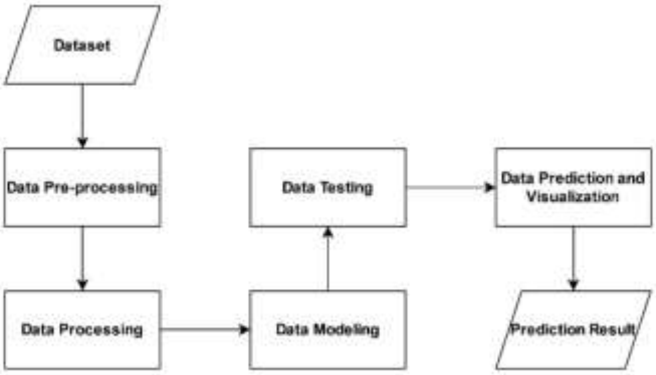


Figure 1. Research Method

2.2.1. Data Pre-processing. In the first process, cleaning the data ensures that all data have the same range and converts it into USD for currency standardization. These steps involve handling missing values, removing outliers, and verifying the integrity of the data. This process aims to prepare the dataset for practical analysis and modeling**.**

2.2.2. Data Processing. The pre-processing transforms the data to be suitable for input into machine learning and deep learning models. This stage involves scaling features to ensure no variable dominates due to scale differences. Additionally, the dataset is split into training and testing sets, typically using a time-based method to preserve the chronological order of economic events. This research allocates 80% of the data for training and validation, reserving the remaining 20% for testing. The details of the dataset splitting appear in the table below.

Table 1. Dataset Splitting

Dataset Part	Data Range	Number of Data Points	Date Range
Training/Validation	1 - 259	259	Jan. 1997 – Feb. 2018
Testing (Holdout)	260 - 324	65	Mar. 2018 – Dec. 2023

For the deep learning models, the data is further processed into sequences, where each sequence comprises data points from nine consecutive months. This approach allows the models to learn from patterns over time, enhancing their ability to predict future economic conditions based on past trends**.**

2.2.3. Data Modeling. This phase employs Machine Learning and Deep Learning techniques to forecast economic indicators, subsequently integrating the results through ensemble learning to enhance prediction accuracy. The ensemble methods include averaging (mean), median aggregation, and a stacked approach, each chosen for its ability to mitigate model-specific biases and variance in predictions.

1) Machine Learning Models - Support Vector Regressor (SVR)
   Support Vector Regressor (SVR) helps predict economic variables because it can model complex, nonlinear relationships between factors. The ability to model nonlinear relationships is vital since economic data often does not follow a straight line (linear pattern). To handle these complex nonlinear patterns, SVR uses a unique mathematical tool called the Radial Basis Function (RBF) kernel, which helps the model understand the nonlinear patterns in the data.

   The RBF kernel helps measure two data points' similarity, even if their relationship is not straightforward. The model's ability to find patterns relies on two critical settings:

   a. C (penalty parameter): This controls how much the model focuses on correctly predicting each point in the dataset. A high value means the model tries harder to predict each point correctly but risks overfitting.

b. Gamma (kernel coefficient): This influences how far the influence of a single data point stretches. A low gamma means far-away points matter more, while a high gamma means only nearby points are considered.

By tuning these parameters, we ensure the model does not become too simple or too complex, balancing accuracy with the ability to generalize to new data.

2) Machine Learning Models - Linear Regression (LR)
Multiple Linear Regression (MLR) is a basic, yet powerful model used to predict a target variable by finding a linear relationship between it and several other factors (features). The linear relationship in MLR means the model tries to draw a straight line (or plane) that best fits the data points. However, MLR can struggle when the features are closely related (a problem called multicollinearity), which might make predictions unstable.

To solve this, we use Linear Regression Ridge (LRR), which improves the stability of MLR by adding a small value (λ) to the calculation. This technique, called regularization, helps prevent the model from becoming too complex or "overfitting" the data. Overfitting happens when the model learns too much from the noise in the data, leading to poor predictions of new data.

The key idea behind LRR is to slightly adjust the importance of each feature in the model by controlling the alpha parameter. This parameter tells the model how much penalize significant coefficients (features with too much influence). By adjusting this parameter, we ensure the model captures essential trends in the data without overreacting to minor variations.

3) Deep Learning Models - Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM)
The CNN-LSTM hybrid model combines two powerful tools: Convolutional Neural Networks (CNNs), which are great at recognizing patterns in spatial data, and Long Short-Term Memory (LSTM) networks, which are excellent for handling data sequences over time. Combining these two neural network types makes the hybrid model especially useful for time-series analysis, where patterns may exist in space (e.g., relationships between variables) and time (e.g., trends over months or years).

a. The CNN part of the model identifies essential features in the data using several layers of convolutions, highlighting key patterns. After that, pooling layers reduce the data size while keeping the most essential information intact.
b. The LSTM part helps the model understand how the data changes over time. LSTMs uniquely remember information using components like the input, forget, and output gates. These gates help the model decide what information to keep, what to discard, and what to use for predictions.

In simpler terms, CNNs identify what is essential, and LSTMs determine how those important things change over time. This combination is particularly effective for financial forecasting, as it captures the critical patterns and the historical trends in the data (Gao et al., 2021).

4) Deep Learning Models - Convolutional Neural Network-Gated Recurrent Units (CNN-GRU)
Like the CNN-LSTM model, the CNN-GRU model combines the strengths of Convolutional Neural Networks (CNNs) and Gated Recurrent Units (GRUs). CNNs identify important spatial patterns in the data, while GRUs handle how the data evolves. GRUs have a more straightforward structure than LSTMs, making them faster and easier to train.

a. The CNN part processes the input data to capture key features, and these features are then passed to the GRU layers.

b. The GRU uses two main components: the update gate (z) and the reset gate (r). These gates control how much information from the past is remembered and how much new input is passed. Unlike LSTMs, GRUs do not have an output gate, making the structure simpler and more efficient (Yamak et al., 2021).

In simpler terms, CNNs find what is essential in the data, and GRUs decide how much of that information should be passed on based on the data's history. This combination makes the CNN-GRU model well-suited for tasks requiring spatial and temporal understanding (Gao et al., 2021).

5) Validation and Robustness
To ensure that the models are reliable, we use 10-fold cross-validation. This method divides the dataset into ten parts, using each part for testing while the remaining nine are used for training. By repeating this process, we make sure that the model performs well across different data samples, helping to fine-tune its parameters and make the results more generalizable.

6) Splitting the Data
The training dataset, consisting of 259 data points (from January 1997 to February 2018), is divided into ten approximately equal-sized folds or subsets.

7) Training and Validation Cycles
In each of the ten iterations of the process, a different fold of the data is held out as a validation set, and the remaining nine folds are used as the training set. This configuration includes each data point in the validation set precisely once and nine times in the training set.

8) Model Evaluation
In each iteration, the model is trained on the training set and evaluated on the validation set. This cycle helps assess the model's performance consistently across different subsets of the data.

9) Ensemble Learning
Final predictions are derived by combining individual predictive models' outputs using ensemble methods, including mean, median, and stacked techniques. Each method integrates insights from multiple models to improve overall forecast accuracy by reducing variance and bias inherent in any single model.

The stacked ensemble is particularly sophisticated among the techniques used. In this approach, the outputs from the primary predictive models (such as CNN-LSTM, GRU-LSTM, SVR, and LLR) serve as input features to a secondary model—a simple neural network. This secondary model is designed to learn the optimal combination of primary model predictions. It does this by training on these inputs in a supervised learning context, where the target is the actual historical GDP data.

2.2.4. Data Testing. At this stage, each model undergoes rigorous testing using a set of data that is entirely new and unseen during the training phase. This approach ensures that the models' performance reflects their ability to generalize to the latest data rather than merely reproducing results from their training set.

1) Error Metrics and Evaluation
We use the Root Mean Squared Error (RMSE) to measure how well the model performs. RMSE is commonly used in forecasting because it gives more weight to significant errors, which is essential when making predictions in economics, where big mistakes can have a significant impact. The formula for RMSE is:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2} \quad (1)$$

This metric is mainly chosen for its sensitivity to significant errors, making it suitable for emphasizing the accuracy of predictions in economic forecasting where outliers can have substantial impacts. The RMSE measures the average magnitude of the model's prediction errors, quantifying how closely the predicted values match the actual economic indicators.

2) Testing Outcomes and Model Comparison
The results from these tests are crucial for assessing the effectiveness of each predictive model. Comparative analysis of RMSE scores across different models objectively evaluates which models perform best under real-world conditions. These insights inform further refinements to the models and guide the selection of the most appropriate model or ensemble method for subsequent economic predictions.

2.2.5. Prediction Data and Visualization. This stage integrates test data processing with the visualization of results, enhancing the comprehensiveness and clarity of the predictive outcomes. After testing, the predictive models generate GDP forecasts, visualized to compare predicted trends against actual historical data. Visualization tools are used to create graphs that depict the effectiveness of the models and highlight any deviations or predictive insights. These visualizations serve not only to validate the models but also to communicate complex results in an accessible manner. By visually comparing the predicted data with actual outcomes, stakeholders can more easily assess the model's accuracy and potential economic forecasting implications.

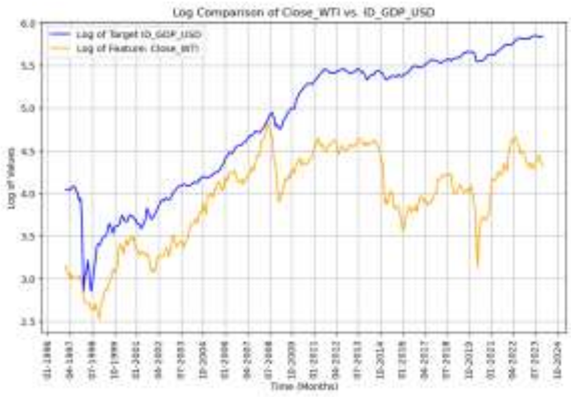
3. Main Findings

This section of the paper delves into a comprehensive analysis of our dataset and the predictive models applied to forecast Indonesia's economic trends. The analysis consists of three parts, each designed to explore different aspects of our data and modeling approach.

3.1. Descriptive Analysis

The first section of the analysis describes the data obtained from this study. Descriptive analysis offers a general overview of the data's condition without rendering any specific evaluations, limiting its use to merely describing the state of the research data [14]. The research data spans from January 1997 to December 2023, encompassing 324 entries across 17 factors. A comprehensive overview of the relationships between each variable and Indonesia's GDP is presented in the figures below. By using graph and diagram visualizations, the relationships between each independent variable (such as gold prices, crude oil prices, USD/IDR exchange rate, Jakarta Composite Index, money supply, inflation, exports, imports, BI interest rate, household consumption expenditure, and gross fixed capital formation) and GDP can be displayed more clearly and intuitively. This visualization allows us to see patterns, trends, and correlations between these variables, for example, whether an increase in one variable is directly proportional to an increase in GDP or vice versa. Thus, the figures provide a more comprehensive understanding of how the independent variables interact with and influence GDP, facilitating identifying relationships that might be difficult to see through numerical analysis alone.

(a)



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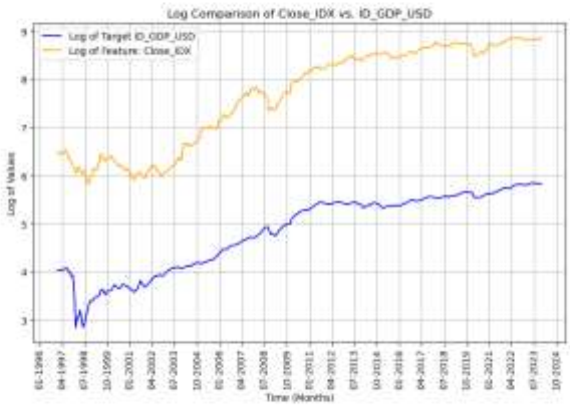
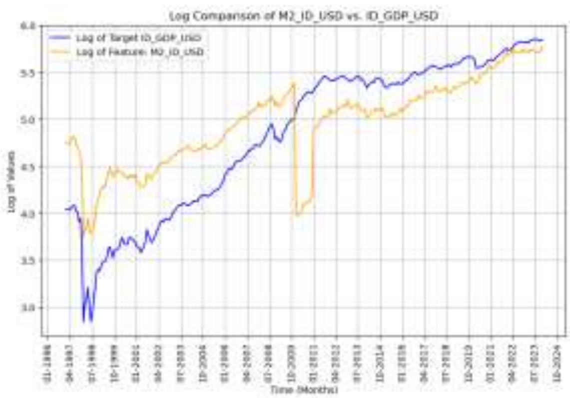


(d)

Figure 2: Comparison of Gold Price (a), Crude Oil WTI Price (b), Crude Oil Brent Price (c), and IDX Composite (d) to GDP of Indonesia

As shown in the figure 2, the trends of gold prices and the Indonesia Composite Index (IHSG) generally display a linear relationship with the rising GDP trend. Meanwhile, the prices of Brent and WTI oil indices exhibit a more random linearity with GDP.



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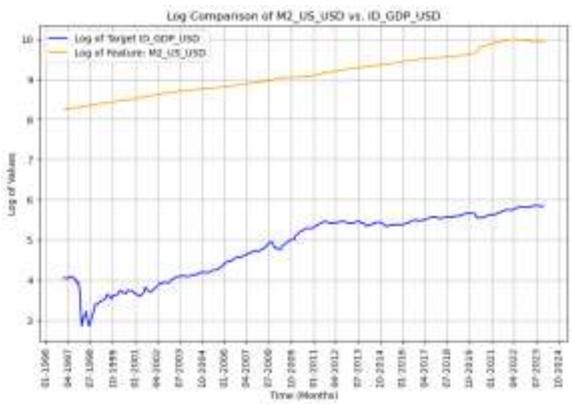

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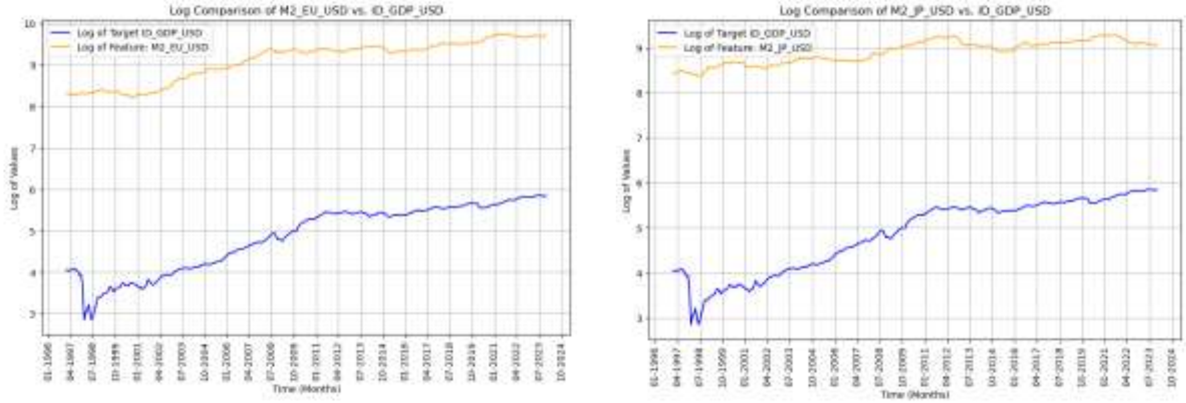
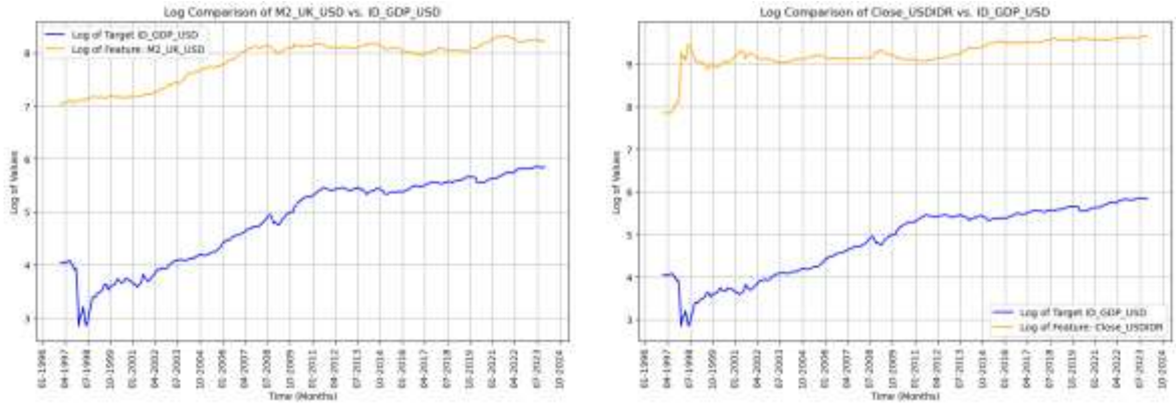


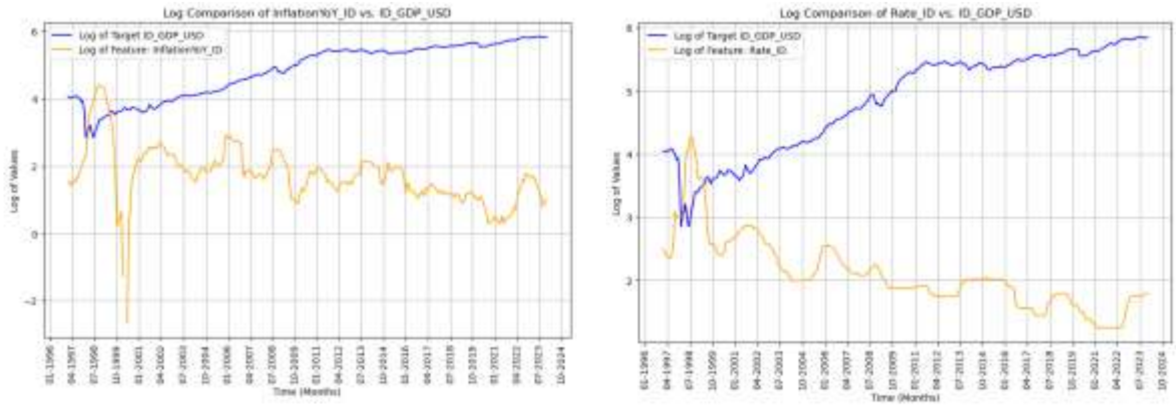
(C) (D)

Figure 2. Comparison of M2 of Indonesia (a), M2 of United States (b), M2 of European Union (c), and M2 of Japan (d) to GDP of Indonesia

The chart above shows in figure 3 that the M2 money supply from Indonesia, the US, Europe, and Japan has a relatively stable linearity with the growth of Indonesia's GDP. Notably, M2 money supply in Indonesia experienced a significant contraction in 2009-2011.



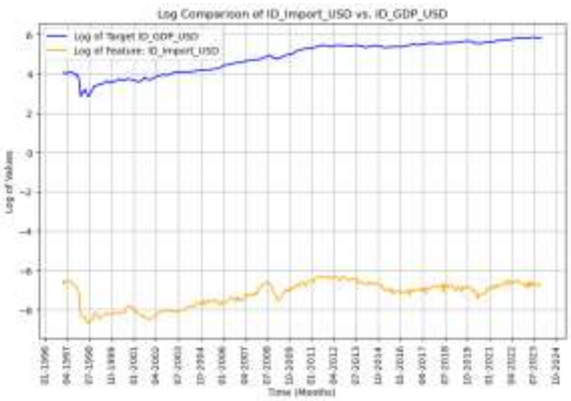
(a) (b)



(c) (d)

Figure 3. Comparison of M2 of United Kingdom (a), Exchange Rate USD to Rupiah (b), Inflation of Indonesia (c), and BI Rate (d) to GDP of Indonesia

The figure 4 show that the M2 money supply from the UK and the USD to IDR exchange rate demonstrate a relatively stable linearity. In contrast, the Bank Indonesia (BI) rate and inflation variables show an inverse relationship model with the value of Indonesia's GDP.



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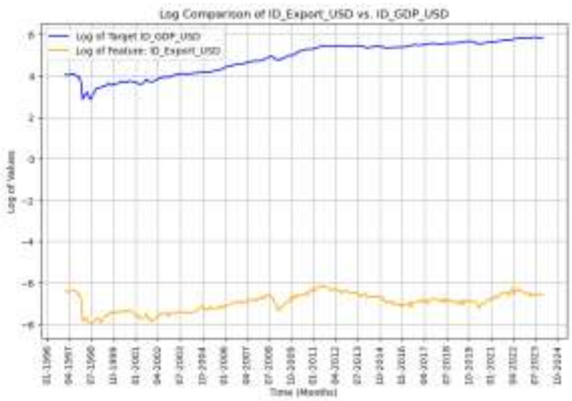

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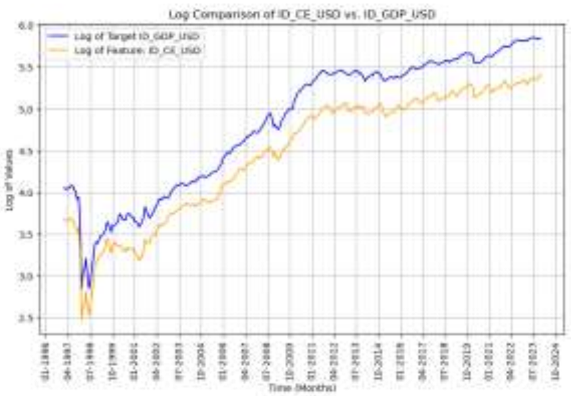

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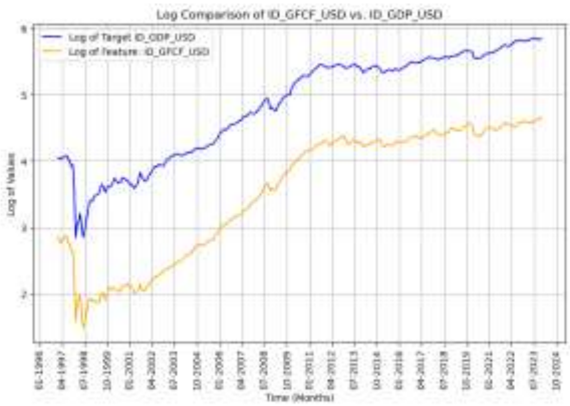

(d)

Figure 4. Comparison of Import of Indonesia (a), Exports of Indonesia (b), Consumer Spending of Indonesia (c), and Gross Fixed Capital Formation of Indonesia (d) to GDP of Indonesia

The above figures also indicate that the variables for Indonesia's imports, exports, consumer spending, and gross fixed capital formation display a linear and stable model histogram relative to the value of Indonesia's GDP.

3.2. Correlation Analysis

Subsequently, this study will perform a correlation analysis using the Pearson Correlation model. The Pearson Correlation Coefficient is a statistical measure quantifying the strength and direction of a linear relationship between two variables [15]. This coefficient ranges between -1 and +1:

a. +1 indicates a perfect positive correlation, where an increase in the other always accompanies an increase in one variable.
b. 0 indicates no linear correlation between the two variables.
c. -1 indicates a perfect negative correlation, where a decrease in the other always accompanies an increase in one variable.

This model is chosen to understand the linear relationships among 16 variables with Indonesia's Gross Domestic Product (GDP). The correlation analysis aims to identify economic patterns that emerge from these variable relationships to Indonesia's GDP growth. Additionally, this correlation analysis measures how strong the linear relationships are between these variables and Indonesia's GDP. The analysis also determines whether these relationships are positive (both variables move in the same direction) or negative (the variables move in opposite directions). The results of the correlation testing are as follows:

Table 1. Pearson Correlation between Macroeconomic Variables and GDP

Variable	Correlation (r)	Relationship	Strength	Interpretation
Gold Price (USD)	+0.95	Positive	Very Strong	Market confidence indicator
Oil Price (Brent)	+0.65	Positive	Moderate	Production & transportation cost
Oil Price (WTI)	+0.98	Positive	Very Strong	Export revenue driver
Exchange Rate (USD/IDR)	+0.60	Positive	Moderate	Export competitiveness
Consumption	+0.78	Positive	Strong	Main GDP driver
M2 Indonesia	+0.88	Positive	Strong	Domestic liquidity
M2 Japan	+0.92	Positive	Strong	Global liquidity spillover
M2 USA	+0.98	Positive	Very Strong	Global financial influence
M2 EU	+0.90	Positive	Strong	International capital flow
M2 UK	+0.87	Positive	Strong	External liquidity
Inflation	–0.35	Negative	Moderate	Purchasing power erosion
BI Rate	–0.55	Negative	Moderate	Investment suppression
Exports	+0.75	Positive	Strong	Direct GDP contributor
Imports	+0.65	Positive	Moderate	Demand & production input
GFCF	+0.95	Positive	Very Strong	Capital formation

The results above show that the relationships between gold prices (r = 0.95), oil prices (Brent r = 0.65; WTI r = 0.98), the Composite Stock Price Index (IHSG, r = 0.98), the USD exchange rate (r = 0.60), M2 money supply (r = 0.87–0.98), imports (r = 0.65), exports (r = 0.75), consumer spending (r = 0.78), and gross fixed capital formation (r = 0.95) with Indonesia's GDP demonstrate how various economic factors interact and influence economic growth. A positive correlation between these variables and the GDP indicates that when one variable increases, the GDP also tends to increase.

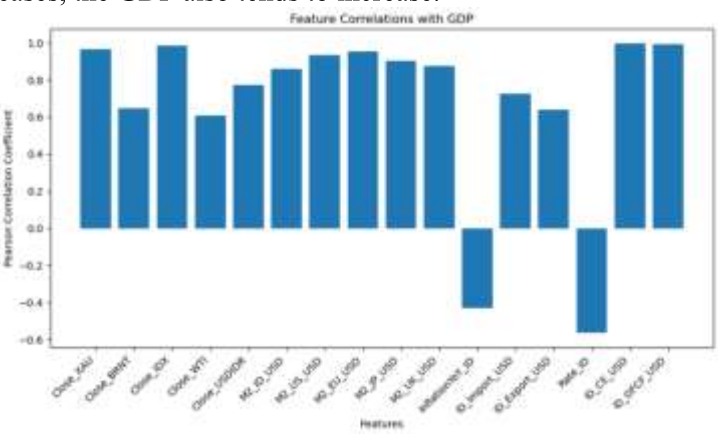

Figure 5. Correlation Analysis of All Features and GDP of Indonesia

For the first variable, gold prices show a very strong positive correlation with GDP (r = 0.95) due to gold being often considered an indicator of market confidence in the economy. When gold prices rise, it may indicate that investors have positive expectations about economic conditions, which usually coincide with GDP growth [5]. Gold also serves as a foreign exchange reserve for the country. Gold price increases can strengthen the country's foreign reserves and financial stability, supporting economic growth. Similarly, oil prices also show a positive correlation with GDP (Brent r = 0.65; WTI r = 0.98) because oil is a significant commodity that affects production and transportation costs. When oil prices are stable or increase moderately, this can reflect healthy economic growth, supporting an increase in GDP. Indonesia is also an oil producer, so rising oil prices can increase national revenue from oil exports, positively contributing to the GDP [6]. The IHSG also positively correlates with GDP (r = 0.98) because it reflects the performance of major companies in Indonesia. An increase in the IHSG indicates that these companies are performing well, typically alongside economic growth. An increasing IHSG attracts more investment, both domestic and foreign. This investment boosts economic activity and consumption, which drives GDP growth [10].

The fifth variable, the USD to Rupiah exchange rate, also shows a moderate positive correlation with GDP (r = 0.60). A stable or weakening USD against the rupiah can make Indonesian exports more competitive and attract foreign investment [16]. An increase in exports and investment raises GDP. A stable exchange rate helps keep foreign debt costs under control, supporting fiscal stability and economic growth. The entire M2 money supply also positively correlates with Indonesia's GDP (r = 0.87–0.98). M2 includes cash and deposits, representing a broad measure of the money supply. An increase in M2 signals greater liquidity in the market, which facilitates more credit and investment opportunities. This surge in liquidity fosters GDP growth by encouraging higher levels of investment and consumption. Monetary policies that expand M2 can stimulate the economy by lowering interest rates and increasing spending [17].

Furthermore, the import and export variables also display a strong positive correlation with GDP (imports r = 0.65; exports r = 0.75). Increased exports directly contribute to GDP since they are a crucial component of its calculation. While imports technically reduce GDP, they often indicate strong domestic demand and investment in technology and raw materials, supporting long-term economic growth. Additionally, an increase in net exports (exports minus imports) directly impacts GDP [18].

The following variable showing a strong positive correlation is consumer spending (r = 0.78). Consumer spending reflects purchasing power and domestic demand. When household consumption increases, it indicates an improvement in economic welfare and drives GDP growth since consumption is the most significant component of GDP [8]. Furthermore, increased consumer spending encourages companies to increase production and investment, accelerating economic growth. Lastly, the variable of gross fixed capital formation in the country also exhibits a very strong positive correlation with GDP (r = 0.95) because gross fixed capital formation reflects investment in infrastructure and other fixed assets. This investment increases production capacity and economic efficiency, promoting long-term growth. Investment in fixed capital creates jobs and enhances productivity, directly contributing to GDP growth (Ministry of National Development Planning/Bappenas, 2023). The positive correlation between these variables and GDP reflects how interrelated economic factors can drive economic growth. Many of these variables tend to increase when the economy grows, reflecting the complex dynamics between consumption, investment, trade, and economic policy [10].

While variables such as inflation and the Bank Indonesia interest rate negatively correlate with Indonesia's GDP (inflation r = –0.35; BI rate r = –0.55) due to several factors. First, high inflation reduces public purchasing power. When prices of goods and services rise, consumers must pay more for their basic needs, reducing the amount of money available for other expenditures. This decrease in consumption, a significant component of GDP, can lead to reduced economic activity. Additionally, high inflation often creates economic uncertainty [7]. Consumers and businesses may delay purchases and investments because they are unsure how long prices will continue to rise or how high inflation will reach. This uncertainty can further slow economic activity.

Meanwhile, borrowing costs for consumers and businesses also rise when BI interest rates rise. Consumer credit, such as home loans, vehicle loans, and credit cards, has become more expensive, which can reduce consumer spending. Likewise, higher borrowing costs for businesses can reduce investment in capital and business expansion. Higher interest rates make business investments more expensive. Businesses may delay or cancel investment projects because of the high cost of capital, which can slow economic growth [5]. Overall, inflation and BI interest rates affect various economic aspects directly related to GDP growth. High inflation reduces consumer purchasing power and increases production costs, while high interest rates increase borrowing costs and reduce investment [17]. Both variables, when increasing, tend to slow economic activity and reduce the GDP growth rate. Therefore, the negative relationship between inflation, BI interest rates, and GDP reflects how price pressures and borrowing costs can suppress overall economic activity.

3.3. Simulation and Predictive Analysis

In the predictive analysis conducted in this research, multiple regression analysis was performed on the previously determined independent variables. Following the research method explained, the data was divided into two parts. The first part covers data from 1997 to 2012, which was used as the basis for training the model (training data). Through this training process, the simulation model was designed to predict Indonesia's economic growth. The second part covers data from 2013 to 2023, which was used as testing data to verify the model's accuracy by comparing the GDP value projections produced by the model with the actual GDP data during that period.

There are three approaches used to simulate economic growth projections: the mean method, the median method, the weighted approach, and the stacking method. Each method was tested to measure the accuracy level of the projection using Root Mean Square Error (RMSE), the standard for measuring prediction error rates. A lower RMSE indicates a more accurate model. The results of the model simulation can be seen in Figure 7 below:

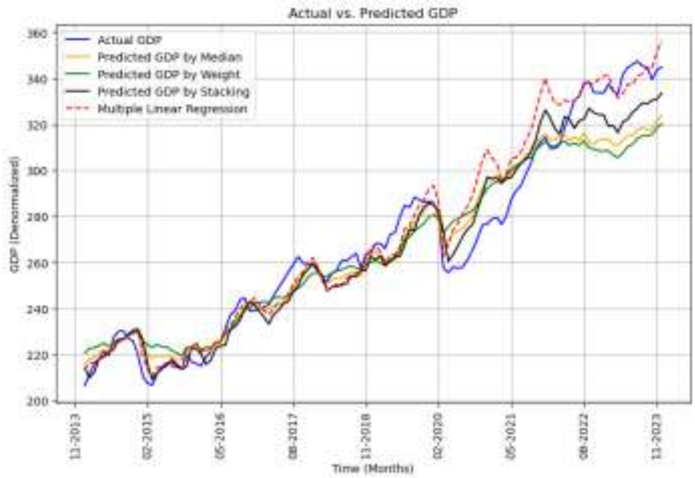

Figure 6. The Result of the Predictive Model using Ensemble Learning

Based on the figure above, we can observe the projection results from the modeling using machine learning and deep learning. Generally, the simulations conducted demonstrate a trend pattern similar to the actual GDP values from 2014 to 2023. The graph shows that the AI simulation projections of GDP values align well with the actual GDP data.

Admittedly, the actual GDP from 2014 to 2015 experienced an increase from early 2014 to late 2014, followed by a decrease at the end of 2014. Machine learning and deep learning simulation predictions similarly depict this pattern. Likewise, between 2015 and 2019, the Indonesian GDP trend increased, although there were several corrections in mid-2016 and mid-2017. Simulation evidence from machine learning and deep learning data processing also predicts this pattern.

At the beginning of 2020, Indonesia's GDP experienced a sharp decline due to COVID-19. This GDP downturn was also successfully and accurately projected by the machine learning and deep learning simulation models, as seen in the comparative graph above. Following the post-COVID-19 period from 2020 to 2024, it is evident that the actual GDP of Indonesia gradually rose and recovered. This trend is precisely depicted by the results of the machine learning and deep learning simulations, showing an increase in GDP values consistent with the actual occurrences.

Through modeling assisted by Machine Learning and Deep Learning, the simulation results show that the AI model can identify and follow the same trend patterns as seen in the actual GDP data from 2014 to 2023. If GDP experiences an increase or decrease during a specific period, this AI model can capture these changes and accurately reflect them in its predictions. This capability is crucial, considering that GDP is a key indicator of economic performance influenced by many external factors such as fiscal policy, monetary policy, global market fluctuations, and domestic conditions. Thus, accuracy in reflecting these trends depends on static data analysis and the model's ability to adapt to complex patterns from various macroeconomic variables. The graph comparing the AI model's predictions with actual GDP values shows a high level of alignment. The consistency of predictions produced by this model also confirms that AI can handle economic data volatility that is often nonlinear and difficult to predict using traditional methods. This graph shows that GDP predictions by the AI model move in tandem with actual values, reflecting the same up-and-down patterns, indicating that the AI model can accurately depict economic dynamics. This approach also demonstrates the superiority of AI in extracting information from historical trends, enabling more accurate projections than conventional statistical models.

Furthermore, the evaluation of model performance, using Root Mean Square Error (RMSE), provides strong evidence for the accuracy and reliability of these predictions. In this study, several approaches were used, and the RMSE results show different levels of accuracy among the methods. The mean method has an RMSE of 12.3772, the median method 13.1354, and the weighted method 14.2175, while the stacking method, which shows the highest accuracy, produces an RMSE of 9.8316.

RMSE measures the error between predicted and actual values, and the lower the RMSE value, the more accurate the prediction model. In this context, an RMSE of 9.8316 from the stacking method is considered very good, showing that the AI model can predict GDP growth with a small error rate. Based on general standards, a predictive model is said to be accurate if its RMSE is close to or less than 10, especially in the context of macroeconomic predictions with a high variability level. The trend alignment depicted by the graph and the low RMSE value proves that this AI approach is highly accurate and reliable in predicting future economic performance. Thus, this model can be relied upon as a tool that aids in future economic planning and decision-making and provides a basis for better economic policies.

Moreover, one of the main advantages of this research is the ability of the AI model to simulate various economic scenarios, including crises or growth surges, and assess the impact of fiscal and monetary policies. Data covering economic crisis periods, such as the 1998 monetary crisis and the COVID-19 pandemic crisis in 2020, shows that this model can maintain prediction accuracy, even in volatile economic conditions. The model's demonstrated accuracy in volatile conditions provides evidence that the developed AI model is resilient enough to face drastic changes in economic conditions, a crucial factor in policy-making. When faced with conditions such as inflation surges, fluctuating interest rate policies, or fiscal stimulus policies, this simulation can help policymakers understand the potential impacts of various interventions. Thus, this model not only projects economic growth in general but also provides a tool to test more specific policy scenarios, enabling more measured and data-based decisions.

The AI simulations utilizing Machine Learning and Deep Learning show trend patterns that are very similar to the actual GDP values from 2014 to 2023, offering several vital impacts in various aspects, including improved decision-making, enhanced reliability in public policy, investment optimization, monitoring of the country's economic health, and creating efficiency and effectiveness in the implementation of national policies [1]. Accurate GDP predictions enable governments, policymakers, and the private sector to make more informed decisions. With reliable projections, the government can allocate resources more effectively, ensuring that public funds are used in the areas that need them most [11]. The government can develop appropriate fiscal policies through these projections, such as adjusting taxes and subsidies to encourage economic growth.

Good budget planning and fiscal policy are directly connected to the community's economic life. They ensure economic stability, effective resource allocation, reduction of social inequality, appropriate investment, and prudent debt management. All these contribute to improving community welfare, price stability, and sustainable economic growth [19]. Thus, sound budget planning and fiscal policy are essential for healthy economic development and community prosperity. Accurate AI simulations assist the government in long-term economic planning and help it make more realistic long-term plans based on accurate economic projections.

Additionally, these simulations help identify potential economic risks early on, allowing for timely mitigation steps. The results of these GDP projections can serve as a means to enhance the quality of the country's economic policies. Policies based on accurate predictions can be implemented more efficiently. Through these simulations, the government can conduct Policy Impact Measurements by evaluating the impacts of policies that have been implemented and making adjustments as needed [13]. At the same time, the government can also develop New Policies by creating more effective policies based on projections of future economic trends.

These efficient and effective economic policies are crucial for the economic life of the community because they support sustainable economic growth, create jobs, reduce social inequality, and maintain economic stability [19]. These policies ensure optimal resource use, enhance welfare, and lay the foundation for a better future. Thus, sound economic policies are crucial to achieving welfare and sustained economic stability for the entire society. Beyond government, for investors and companies, GDP forecasts can help devise investment strategies and assess risks [11]. Corporate projection simulations provide a basis for formulating better projection simulations can also more accurately evaluate investment risks, thus avoiding sectors that may experience declines. The accuracy of these GDP projection simulations also provides a foundation for foreign investors to feel confident in investing in Indonesia. Through these projections, foreign investors can monitor a country's economic health [20]. The simulations provide more accurate reports to international institutions and investors about the economic health of Indonesia.

These projections also serve as an appropriate tool for understanding long-term economic trends. They can analyze factors influencing changes in a country's economic conditions, such as trade policy shifts or global market fluctuations. By providing a precise analysis of these trends, Indonesia enhances its appeal to foreign investors. Foreign investors are vital for community economic growth as they bring capital, technology, and new knowledge that accelerate economic development [21]. They create jobs, enhance the local workforce's skills, drive innovation, and increase economic competitiveness. Additionally, foreign investment boosts tax revenue and economic stability, contributing to societal welfare [22]. Therefore, attracting foreign investors is a primary strategy for governments to promote sustainable and inclusive economic growth.

4. Concluding Remarks

This research develops an integrated simulation model for projecting Indonesia's GDP using key macroeconomic determinants, including commodity prices, financial indicators, monetary variables, trade components, consumption, and capital formation, combined with machine learning, deep learning, and ensemble approaches. The results demonstrate that the proposed model is capable of capturing complex economic dynamics and producing highly accurate projections, as indicated by the superior performance of the stacking ensemble method with an RMSE of 9.8316. The strong alignment between predicted and actual GDP trends confirms the reliability of artificial intelligence in modeling nonlinear and volatile macroeconomic patterns.

Furthermore, the findings highlight the practical value of AI-based simulation models in supporting evidence-based economic policymaking. Accurate GDP projections enable policymakers to design more responsive fiscal and monetary strategies, optimize resource allocation, and improve risk mitigation planning. By linking dominant economic predictors with policy instruments, this framework provides a quantitative foundation for strengthening long-term economic governance and development planning in Indonesia.

Despite these contributions, this study has several limitations. First, the use of aggregated macroeconomic data may introduce aggregation bias, which can obscure sector-specific dynamics and regional disparities. Second, the model has not been extensively tested under alternative stress-testing scenarios, such as extreme financial shocks or prolonged global recessions, limiting its ability to fully evaluate resilience under severe economic disruptions. Third, the selected machine learning and deep learning architectures may not capture all forms of structural changes in the economy.

Future research is therefore recommended to incorporate disaggregated sectoral and regional data, develop systematic stress-testing frameworks, and explore alternative modeling techniques to enhance robustness and generalizability. Expanding the scope of analysis to ASEAN and Asia-Pacific regions may also improve cross-country validation and strengthen the applicability of AI-based economic simulation models.

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