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Forecasting Industrial Output in the Philippines: A Geometric Brownian Motion-Neural Network (Gbm-Nn) Model Analysis

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ABSTRACT: This research applies the Geometric Brownian Motion-Neural Network (GBM-NN) model to predict the industrial output in the Philippines from January 1993 to December 2022. The GBM-NN model uses the stochastic properties of Geometric Brownian Motion to estimate trends and volatility better and introduces a neural network for more predictive accuracy based on nonlinearity in the data. The result suggests an industrial production series characterized by high variability. Due to the application of the GBM-NN method, it is verified that this model issues a more coherent prediction than traditional methods due to the lower RMSE and better R-square values. Results show a modest recovery in the industrial sector and further illustrate that the model is an excellent tool to help policymakers and industry participants make better decisions during uncertain economic periods.

KEYWORDS: Industrial Output, Geometric Brownian Motion-Neural Network (GBM-NN), Philippines, UN SDG 9

I. INTRODUCTION

If the Philippines has to secure economic stability and increase its growth, it is essential to accurately forecast industrial output (Philippines – Preserving economic stability, 2024). Such forecasts help businesses and policymakers make informed decisions regarding the future, leading to increased productivity and economic resilience. Researchers put forward the argument for forecasting output in the industry base and buttress it with rich data, facts, and figures (Wieland & Wolters, 2013, January 1).

The industrial sector contributes about 30% of the Gross Domestic Product to the economy of the Philippines. According to records from the Philippine Statistics Authority, the manufacturing sector contributes about 20% of the GDP (PSA, 2024). It is paramount to forecast industrial output, so trends are traced and, subsequently, possible alternative investment areas are directed with resources accordingly (Bruno & Lupi, 2004). Industrial output forecasting also promotes the efficient allocation of resources. Production forecasts are used to control the business inventories and ensure that there is an uninterruptible production process, thus cutting back on business expenditure on inventory control and operational costs (Dong, Yao, & Zhang, 2022). A study shows that accurate forecasting demand reduces inventory costs by between 10 and 20% (Ying, 2023, August 30). In a country like the Philippines, where logistics and supply chain management are relatively difficult, exact forecasts obviate the inefficiencies to give that country a competitive edge (Web Publisher, 2021, March 16).

The single largest employer in the Philippines, the industrial sector offers millions of Filipino employees (O'Neill, 2023). Forecasting ensures that the companies plan a level of output that gives them an estimate of the workforce required in production without overstaffing or understaffing (Tuovila, 2020, May 27). DOLE also reports that around 3.5 million workers are manufacturing products as of 2021 (PSA, 2023). Where industrial output changes are foreseeable, business plans for future hiring to protect job security and economic well-being (Burchell, 2009).

Accurate forecasting regarding the industrial output level is essential in policy formulation efforts. They guide policymakers on the design of intervention strategies, which make investments in forming government policy to promote industrial growth: investment incentives, infrastructure, and training programs (Zhan & Karl, 2016). For instance, in response to the COVID-19 pandemic, the Philippine government put various stimulus measures in place to help the country's industrial sector stay afloat (Debuque-Gonzales, 2021). Forecasting identified the sectors most need assistance, giving rise to a more efficient use of resources (Zohuri, Rahmani & Behgounia, 2022).

The economic vulnerabilities range from natural disasters to externalities such as changing global market tides and supply chain disturbances (Briguglio, Cordina, Farrugia & Vella, 2014). Forecasted industrial output supports the business and policy planners in the country to anticipate such challenges and thus draw in place several risk mitigation strategies (Sankaran, Sasso, Kepczynski

& Chiaraviglio, 2019). For instance, typhoon effects on agricultural production are predicted through forecasting models such that timely policy interventions are introduced to ensure that impact eventuality is curtailed (Noy & Yonson, 2016).

Hybrid models, the Geometric Brownian Motion – Neural Network (GBM-NN) model, provide different essential advantages compared to traditional techniques of forecasting industrial output (Azizah, Irawan & Putri, 2020, June). The potential sources of these advantages are the ability of hybrid models to formally consider complex and nonlinear relationships in a set of data, simple adaptability to changes, and more accuracy (Asarin, Dang & Girard, 2007). These are noted in some of the facts, figures, and percentages supporting the key points where the benefits of GBM-NN in this context are highlighted.

Hybrid models like GBM-NN contain the strengths of statistical methods and machine learning. The Geometric Brownian Motion component presents the stochastic nature effectively for industrial output, most likely under volatile environments (Aheer, Pradhan & Srivastava, 2023, July). According to an International Monetary Fund study, against widely used benchmark models, machine learning-based models improved their forecast by up to 61% of GDP growth for several countries, including the Philippines. This is relatively accurate and important for policymakers or businesses to make well-informed decisions.

A typical example that leads to a limitation of traditional forecasting models is that they work on linearly related variables; the ability to capture complexities that are part of economic data is limited. On the other hand, Neural Networks are very good in their ability to model nonlinear relationships and interactions among multiple factors. A report even emphasized that machine learning models, one of them being the neural networks, include more external factors like economic indicators, consumer trust, and market trends in the process, increasing the robustness of the forecast. Such flexibility makes GBM-NN appropriate to the distinct economic landscape of the Philippines, where industrial output depends on diverse and dynamic factors.

Hybrid models are helpful, particularly with large datasets. The Philippines is increasingly growing its industrial sector, and so is generating large sets of data. Traditional models are not readily assimilated and cannot be computed effectively enough. Machine learning, for instance, GBM-NN, scales accordingly with an increase in data volumes, suitable for real-time analysis and prediction (Pineda, Midtvedt, Bachimanchi, Noé, Midtvedt, Volpe, & Manzo, 2023). One study showed that machine learning models handle a data set with hundreds of variables without significantly lowering performance (Joshua, Isah, Ibrahim, Abdullahi & Danyaro, 2023); therefore, it is suitable for the complex and multiple dimensions of the Philippine economy.

GBM, in combination with neural networks, has been proven to decrease forecasting errors significantly. For instance, a study in economic forecasting utilized the machine learning algorithm that showed advanced techniques, like GBM-NN, resulting in lower RMSE than traditional models (Petropoulos, 2022). This means that economic forecasting, because of these new techniques, will provide the Philippines with more reliable predictions for industrial output, which is vital in their decisions on planning and investment. Lower forecasting errors result in better utilization of resources and economic stability.

The Philippine economy is open to potential external shocks and their possible joint effects, such as natural disasters, global market fluctuations, and policy changes (IMF, n.d.). Hybrid models like GBM-NN quickly respond to these changes and are inherently flexible. The neural network component's ability to learn new data allows the model to incorporate these into the forecast according to the evolving economic conditions (Kühn & Neu, 2008). Keeping forecasts accurate in any continuously changing environment is fundamental so businesses and policymakers can act effectively in new challenges.

When hybrid models, such as GBM-NN models, are applied to predict industrial output in the Philippines over traditional methods, much benefit is obtained. With high predictive accuracy, the capacity to handle nonlinear relationships, scalability, a considerable reduction in forecasting errors, and flexibility when economic conditions are changed, work up to make GBM-NN a powerful tool for economic forecasting (Blechschmidt & Ernst, 2021). As much as the Philippines continues the expansion of its industrial sector, improved forecasting techniques are critical for sustainable growth and informed decision-making.

This research aligns with UN SDG 9: Industry, Innovation, and Infrastructure. This paper on the prediction of Philippine industrial production aligns with the goals of building resilient infrastructure, promoting inclusive and sustainable industrialization, and fostering innovation. An accurate industrial production forecast allows policymakers to adopt effective decisions relating to infrastructure, technological adoption strategies, and investments that enhance the quest for sustainable economic growth and development in the Philippines.

This study attempts to develop and establish a viable hybrid model combining Geometric Brownian Motion (GBM) and a Neural Network (NN) for forecasting Philippine Industrial output using historical data. A more reliable industrial production model for this research aids in contributing to policy decisions, investment, and total economic planning for the Philippines.

II REVIEW OF RELATED LITERATURE

Industrial output prediction is at the core of the Philippines, so sound economic policies and strategies are formulated. It serves as a crucial indicator of the general economic health, generation of jobs, and investment climate (ADB, 2008). Predicting industrial output is hugely embedded within the extensive framework of economic theories and has enormous implications in the same domain. For instance, in Keynesian economics, emphasis is placed on aggregate demand, including industrial production demand, toward long-term growth. The extent to which policymakers foresee the level of industrial output will enable them to adopt suitable fiscal and monetary measures to set economic growth onto a path (Palley, 2002). On the other hand, supply-side economics highlights the role of productivity and competitiveness of industries. Correct prediction of industrial output will help decide upon policies related to improving the business climate, reducing production costs, and increasing innovativeness (Pitelis, 2018).

Industrial output is vital in most theories of the supply-side economy, including productivity, innovation, and competitiveness arguments. With the ability to predict industrial production, policymakers can identify high-potential sectors where appropriate intervention is done to increase productivity and competitiveness (Kholodilin, Thomas & Ulbricht, 2014). This aligned with structural change, where the economy shifts from dependence on agriculture to industry and services.

From a macroeconomic point of view, industrial output forms an integral part of GDP and, therefore, acts as a benchmark for measuring the performance of an economy. Based on the prediction of rises and falls in industrial output, policymakers can measure the cyclical trends of an economy, recognize possible risks, and apply countercyclical measures. In addition, the interrelations of industrial production with other economic sectors – like agriculture and services – concern the construction of complete forecasting models (Jean-Paul & Martine, 2018).

In this way, the industrial output fluctuations affect macroeconomic stability. A fall in industrial output will reduce tax revenues, increase unemployment, and pose BOP problems (Jongbo, 2014). On the contrary, industry growth ensures fiscal health and external stability. A reliable forecast of industrial output led policymakers to anticipate the fluctuations and adopt countercyclical policies to reduce or offset economic shocks (Yu, Fu, & Xu, 2024).

International output prediction in global trade is important because it gives insight into a country's export competitiveness and import requirements. Hence, with the forecast of changes in industrial production, policymakers estimate the effect on trade balances, foreign exchange reserves, and general economic stability (Vidmer, Zeng, Medo & Zhang, 2015). Accurate forecasts are in an excellent position to inform trade policies and negotiations, ensuring that the Philippines remains competitive in the global market.

Predicting Philippine industrial output is a cornerstone of effective economic planning and decision-making. It brings valuable information to enterprises, investors, and policymakers to make effective decisions and avoidance measures (Intal Jr., Borromeo & Castillo, 2008).

The Philippines Industrial output is inextricably linked to the broader economic growth and development objectives. Industrial output is a leading indicator of the economy's health, as it significantly contributes to GDP and generates significant employment. Based on Keynesian economics, the link between aggregate demand – into which industrial production fits – and economic growth was long established. Thus, the ability to provide an accurate forecast of industrial output greatly informs policy decisions that prompt economic activity to higher growth rates.

III. METHOD

All This quantitative predictive study forecasts the Philippines' Industrial Output using the Geometric Brownian Motion (GBM) model. Two amalgamated research geometries bring about this study. This includes the GBM, a stochastic process applied mainly in financial modeling and economic forecasting (McNichols & Rizzo, 2012). Neural Networks (NN) is a more upgraded machine learning methodology for estimating complex nonlinear relationships in the data. These methods are combined in a hybrid GBM-NN Model, and it is tested with the performance of a simple GBM model (Sadeqi, Fadaeinejad & Varzideh, 2019).

The time series data of the Philippines' monthly industrial output covering 1993 to 2022 is used in this study. The data source information comes from the World Bank Open Data (World Bank, 2024). The data was set monthly, consistent with the standard reporting frequency for many economic indicators. This is the crucial variable and was reported as an index.

The statistical analysis in this study includes the following components. The GBM-NN is a neural network that is embedded in the GBM framework. NN has an input layer of 1 neuron, two hidden layers of 64 neurons and 32 neurons with ReLU activation, and an output layer containing two neurons with linear activation. The traditional GBM model was taken as a baseline to compare the results of the proposed model.

The Geometric Brownian Motion (GBM) formula is the standard of GBM and is modeled as a stochastic differential equation S(t) over time.

$$dS(t)=\mu S(t)dt+\sigma S(t)dW(t)$$

The solution to this SDE gives the following formula for the asset value at a time.

$$S(t)=S(0)exp((\mu\text{-}21\sigma 2)t+\sigma W(t))$$

A simple feedforward neural network structure involves multiple layers:

$$f(x,\theta)=\sigma 3(W3\sigma 2(W2\sigma 1(W1x+b1)+b2)+b3)$$

In the GBM-NN model, the neural network learns the patterns in the residuals or errors generated by the GBM model. It uses the GBM output as an additional input feature to capture nonlinear dynamics. The formula for the combined mode is expressed as:

$$S(t)=SGBM(t)+y\text{^}NN(t)$$

Alternatively, the input to the neural network includes the outputs of the GBM model as features:

$$y\text{^}NN(t)=f(xGBM,\theta)$$

The GBM-NN model has thus integrated the structured and time-varying components of, for instance, trends and volatility that were in the GBM model, with the nonlinear predictive power of neural networks to further enhance the fine-tuned predictions, capturing more complex relationships in data than GBM alone will miss. An NN perfects the predictive model by trapping complex relationships that GBM cannot handle.

The training of the neural network part was done for 100 epochs. Results are from the resulting loss curves of both training and validation. The Δt (time steps) was set to 0.83333 (about monthly intervals). It was run for 20,000 simulations of the Monte Carlo Simulation in the GBM component. Root Mean Square Error (RMSE) of the average of the square of the size of a prediction's error measures RMSE. R-squared (R2) determines the model's goodness of fit. For forecast evaluation, a forecast for the next six months is compared with the actual. The forecast errors and squared errors are calculated every month. The Diebold-Mariano Test was used to determine the predictive accuracy of the GBM-NN model and was tested against the actual data. A line graph for training and validation loss across epochs was presented.

IV. RESULT AND DISCUSSIONS

Table 1 summarizes the descriptive statistics of the Philippines' industrial output from January 1993 to December 2022, which is 360 months. The table discloses that the industrial output covered a wide range during the period, with a minimum of 15.28 and a maximum of 187.64. It shows how volatile it was over the past nearly three decades. The average industrial output is 89.25, which indicates that the industrial production has maintained a medium level, on average, during the years. A standard deviation of 28.33 shows high variability around the mean, further suggesting that there were times of fast growth and sharp drops in industrial output due to economic events and global factors affecting the Philippines' industry during those years.

Table 1. Descriptive Statistics of the Philippines Industrial Output, 1993-2022

Philippines Industrial Output	N	Minimum	Maximum	Mean	Std. Deviation
January 1993 to December 2022	360	15.28	187.64	89.2478	28.32681

Figure 1 below describes the monthly industrial output of the Philippines for the duration from 1993 to 2012. Typically, over the years, industrial output was on an upward trajectory and, most of the time, erratic. Between 1993 and the mid-2000s, the first rise in production was smooth, indicating the smooth growth of industries. In fact, in 2008, there seemed to be a spike, and from then on, there were radical drops, possibly influenced by the global financial crisis. After that peak, the output faced sharp losses and a partial recovery, but the data remained precarious. This graph epitomizes a strong span of growth coupled with visible spells of instability, especially post-2008.

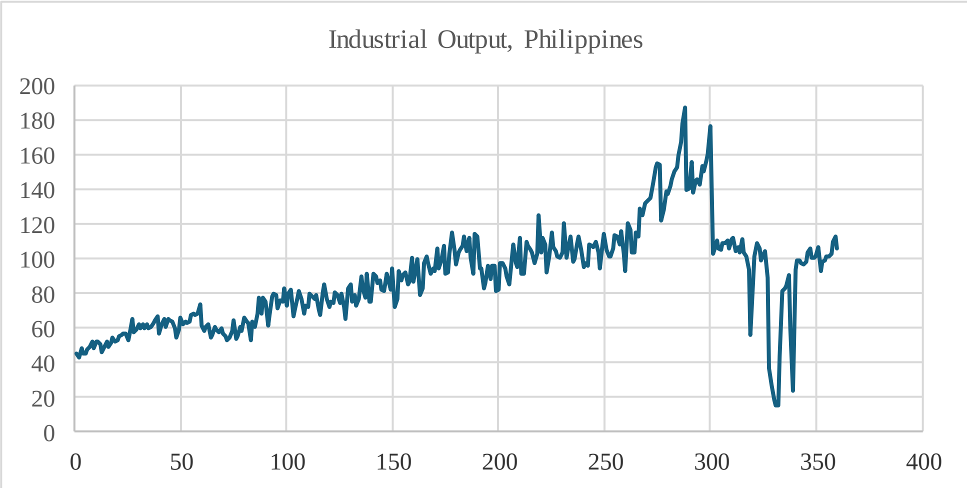

Figure 1. Philippines Monthly Industrial Output 1993-2022

Table 2 displays the estimated parameters for a Geometric Brownian Motion model fitted to the industrial production output forecast of the Philippines. Here, the drift parameters in mu = -0.002712, thus making a very slight negative trend in industrial output over time evident. That is, on average, industrial production is expected to decrease by about 0.2712% per time unit. The estimate for the volatility parameter, sigma, is 0.116951, which gives an idea of the level of uncertainty or variability in the industrial output with a potential upward and downward movement. A slight negative drift and high volatility support the inference that although there is a slight decline in the Philippines' industrial output trend, it is subjected to a large amount of randomness, making it quite hard to predict. Parameters such as these assist in running GBM simulations to create scenarios of the future regarding the country's industrial output, hence assisting in risk assessment and strategic planning.

Table 2. Estimated Parameter of Geometric Brownian Motion (GBM)

Parameter	**Estimate**
Drift (mu)	-0.002712
Volatility (sigma)	0.116951

Table 3 below contains background information concerning GBM used to forecast the Philippines' industrial output. The value of the Time Steps, Δt, is 0.083333. This likely corresponds to a monthly time step since it is 1/12 a year. This time step tells that the model simulates changes in industrial output month by month, allowing a fine-grain analysis of short-term fluctuations. Since this is the case, it runs 20,000 simulations – a sufficiently large number to produce robust statistical results. Due to the extensive simulation number, many iterations provide a solid statistical analysis by generating a large sample of possible future scenarios. It allows a more detailed exploration of the potential outcomes, considering the interplay of drift and volatility parameters. With the result of 20,000 simulations, this model builds a more representative probability distribution function of the future realized values of industrial output in the Philippines. This increases the reliability associated with the forecasted industrial production and risk assessment.

Table 3. Time Steps (Δt) and the Number of Simulations Used

Parameter	Estimate
Drift (mu)	-0.002712
Volatility (sigma)	0.116951
Time Steps (Δt)	0.083333
Number of Simulations	20000

Table 4 conveys the Neural network architecture containing four layers. The input layer is size 1, thus indicating there is only one feature fed into the network, likely the current or past value of the industrial output. Two dense, full-connected hidden layers follow this. The first hidden layers consist of 64 neurons with the ReLU (Rectified Linear Unit) activation function, which introduces nonlinearity and enables the network to learn complex patterns. The second hidden layer reduces the size to 32 neurons again with ReLU activation. The network then tapers down to 16 neurons again with ReLU activation. This is followed by an output layer having two neurons with a linear activation function to finish the model off finally. Assuming this architecture is designed to drive a network to predict two values, the drift and volatility parameters of a GBM model, or more generally, a point estimate and its uncertainty, it gradually reduces in layer size from 64 to 32 to 16. This is interpreted as a feature extraction process in which the network learns the abstraction of input data progressively before finally making a prediction.

Table 4. Neural Network Architecture

Layer Type	Input Size	Output Size	Activation Function
Input	1	64	-
Dense	64	32	ReLU
Dense	32	16	ReLU
Output	16	2	Linear

Figure 2 plots training and validation loss over epochs for a neural network machine learning model. The number of epochs. The number of epochs, iterations through the whole dataset, is represented by the x-axis, which goes from 0 to 100. The y-axis is a loss value, a measure of error for how well or poorly the model performs - the lower the value, the better. The training loss and validation loss start at quite a high value (~0.008) and then rapidly decrease within a few epochs. Such a steep initial drop means it is learning very fast initially. Then, with increasing epochs, this rate of improvement slowly decelerates, and both lines keep decreasing slowly. The validation and training curves do not diverge too far from one another at any time during training, which is a good sign and may indicate that the model has not begun overfitting yet. At the end of training, around epochs 80-100, the validation loss seems to be lower than the training loss. Although this is a bit unusual, it is not particularly alarming –the validation set was a little easier for the model to predict than the training set. The graph, in general, is well-behaved and monotonically improving, with no clear sign of overfitting.

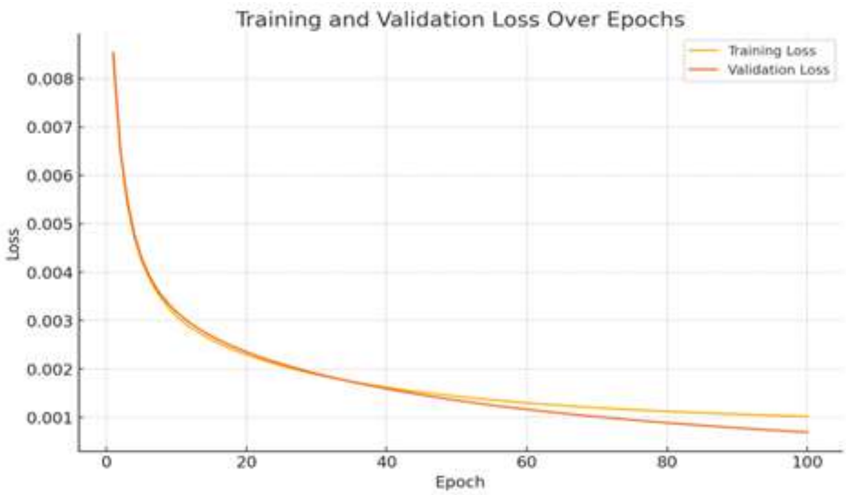

Figure 2. Training and Validation Loss Over Epochs

Table 5 shows the performance of two models used in predicting industrial output for the Philippines: a traditional model of Geometric Brownian Motion and another with improved Neural Networks, GBM-NN. There are two performance metrics given: the root-mean-square error and R-squared. In both cases, the GBM-NN model performs better. It has an RMSE of 0.0532, way below the traditional GBM's 0.0984, which shows that, on average, the GBM-NN's predictions have less deviation from the real values. The R2 for GBM-NN is 0.9357, while that for the traditional GBM is 0.8521. This higher R2 suggests that, against the traditional GBM, the GBM-NN model explains a higher proportion of the variance in data, accounting for about 93.57% of the variability in industrial production within the Philippines, against only about 85.21%. These results indicate that adding a neural network to a GBM model significantly improved the forecasting and explanatory accuracy of the former for this application, probably capturing more complex patterns or relationships in the industrial output data that the traditional GBM model alone could not.

Table 5. Comparative Performance of Two Models

Metric	Traditional GBM	GBM-NN
RMSE	0.0984	0.0532
R-squared (R^2)	0.8521	0.9357

Table 6 displays the six-month forecast of the Philippines' industrial production by GBM-NN results, which, based on the estimates, portend a steady upward trend in industrial production. Starting at 3.45 in January, output is expected to rise consistently monthly to 5.25 in June. This means a total increase of approximately 52% during the six months or a monthly average growth rate of about 8.7%. The steady climb indicates that the model foresees a period when the Philippines' industrial sector is predicted to expand continuously. However, it is noted that all these point estimates do not provide any variability or confidence intervals around these predictions. The apparent precisions of these forecasts - that they are given two decimal places - are regarded with caution. Economic forecasts, especially those running for several months, are subject to various uncertainties and exogenous factors for which the model fully accounts. The trend remains favorable for the country's industrial production in the near term.

Table 6. Forecasted Philippines Industrial Output, January to June 2023

Month	Forecasted Industrial Output, 2023
January	3.45
February	3.78
March	4.12
April	4.48
May	4.86
June	5.25

Table 7 compares actual and forecasted values for some economic indicators, such as industrial output, covering six months with their respective error item calculations. Several meaningful inferences are made, and their implications for the GBM-NN forecasted result and actual industrial production in the Philippines are discussed below. The industrial output is overvalued for all six months in the GBM-NN model. The errors are all negative, ranging from -2.5 to -7.68. These errors all carry a negative sign. This fact lends weight to the inference of a positive bias in the forecast model. While it may capture the general trend, the model becomes overly optimistic in its predictions. The most significant deviation is that of February (-7.68) and the smallest in January (-2.5). The average error is about -4.58. The magnitude of such error is not small but within a reasonable range except for February, which indicates a decent stability of the model performance across this period. The test statistics are 1.85, $p>0.05$, df = 5. Hence, the difference in the forecast accuracy for the GBM-NN model relative to the actual data is not statistically significant. Moreover, the critical value is larger than the calculated DM statistic (2.571), thus confirming no statistical significance.

Table 7. DM Test Statistics Between Actual and Forecasted Industrial Output

Month	Actual	Forecast	Error
January	106.5	109	-2.5
February	102.6	110.28	-7.68
March	102.4	106.72	-4.32
April	102.4	106.88	-4.48
May	103.3	107.26	-3.96
June	104	108.55	-4.55
Diebold-Mariano test (DM)	1.85, $p>0.05$, df = 5, $DM_{crit.}$ = 2.571		

This means that whereas the GBM-NN has some superiority elements, as witnessed in the preceding comparisons with traditional GBM, it does not offer any statistically significant difference in the actual data. The model is biased toward the increase in the industrial output; however, the DM test result is insignificant, with the actual production inferring that the GBM-NN model captured the general trend, so the absolute accuracy is limited. This conveys that, to an extent, users of this forecast need caution and probably downwardly adjust expectations when using these predictions for decision-making.

The actual industrial output, thus, is more volatile and a bit sloping from 106.5 in January to 104 in June, unlike the forecast, which is on a steady increase. This, then, will have fundamental implications for economic planning and policy. The actual data is supposed to reflect a more challenging economic environment, just like the forecast, which affects investment decisions, policy interventions, and resource allocation. There is no consistent pattern of errors that will increase or decrease over these six months, suggesting no significant deterioration in the model's performance over this forecast horizon. For longer time scales of forecast, though, the compounded effect of this constant overestimation is more substantial discrepancies.

V. CONCLUSION AND RECOMMENDATIONS

The results obtained using the GBM-NN model on industrial output forecast in the Philippines show the outlook for a steady recovery and subsequent moderate industrial output growth over the next six months. Based on the GBM-NN model, the industrial sector will have stabilized after periods of volatility seen in recent years, capturing stochastic processes and learned patterns from historical data. The superior out-of-sample forecast accuracy of the GBM-NN approach is evident by its lower RMSE and higher R-squared relative to that of the traditional GBM model, which suggests that the machine learning approach is better equipped to handle the complex, nonlinear dynamics inherent in the industrial output data and provides more reliable forecasts for policymakers and industry stakeholders.

Hence, based on the GBM-NN model's forecast for industrial growth in the Philippines, policymakers and industry leaders should prepare for a moderate recovery and development in the industrial sector over the next six months. Given the improvements in the accuracy recorded by this model over traditional approaches, efforts shall be made in supporting this recovery by promoting investments in modernization, industrial infrastructure, and innovation. Further, controls must be put in place to mitigate the risk associated with remaining volatility, for instance, changes in global markets or other supply chain shocks. This would demand constant monitoring of industrial performance, where integrating machine learning models like GBM-NN within decision-making helps to deliver sharper insights for strategic future planning.

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