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Deep Learning and Neuro Evolution Method for Enhancing Productivity Analysis in Indonesia's Automotive Industry

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Abstract: This study explores the application of Deep Learning and Neuro Evolution to enhance productivity analysis in Indonesia's automotive industry. Deep Learning and Neuro Evolution an advanced AI method, is employed due to its superior capability in automating the selection, optimization, and tuning of machine learning models, making it the most suitable approach compared to other AI methods developed worldwide. By leveraging Deep Learning and Neuro Evolution, we aim to identify and optimize the key factors affecting manufacturing productivity, including foreign direct investment, energy use, gross fixed capital formation, research and development expenditure, and total labor force. Using data spanning from 2003 - 2022, the automated approach facilitates the handling of complex and large datasets, ensuring a comprehensive analysis of how these variables impact value added per worker in the industry. The results indicate that Deep Learning and Neuro Evolution models outperform traditional methods, yielding a Mean Squared Error (MSE) of 0.012 and a Mean Absolute Percentage Error (MAPE) of 1.6 %. These findings provide actionable insights for policymakers and industry stakeholders to foster a more productive and competitive automotive sector in Indonesia.

Keywords: Deep Learning, Neuro Evolution, Productivity Analysis, Automotive Industry Indonesia, Foreign Direct Investment (FDI).

INTRODUCTION

The automotive industry stands as a vital pillar of Indonesia's economy, contributing significantly to GDP, employment, and industrial development. However, like any complex economic sector, it grapples with multifaceted challenges, particularly concerning ownership structures and productivity levels. In this introductory section, we explore the economic underpinnings of these challenges and elucidate why AI emerges as a potent solution. (Smith & Johnson, 2022)

Ownership dynamics in the Indonesian automotive industry present a nuanced landscape, characterized by a mix of domestic and foreign ownership. While foreign direct investment (FDI) has injected capital, technology, and managerial expertise, it has also raised concerns about ownership structures and their impact on productivity. Domestic firms may face challenges in competing with foreign-owned entities, stemming from differences in technology adoption, access to finance, and economies of scale. Consequently, understanding the interplay between ownership structures and productivity is crucial for fostering a competitive and sustainable automotive industry in Indonesia. (Smith & Johnson, 2022)

From an economic perspective, the adoption of AI offers compelling advantages for addressing the challenges posed by ownership dynamics and productivity in the automotive industry. AI-driven analytics enable a granular understanding of the factors influencing productivity, facilitating informed decision-making by policymakers and industry players. By leveraging vast amounts of data, AI can uncover hidden patterns, identify causal relationships, and predict future trends with a level of accuracy and efficiency beyond traditional econometric methods. (Lee & Song, 2020)

Furthermore, AI serves as an economic enabler, fostering innovation, efficiency, and competitiveness within the automotive sector. By automating routine tasks, optimizing resource allocation, and enhancing predictive capabilities, AI unlocks new opportunities for productivity growth and value creation. Moreover, AI-driven insights empower policymakers to design targeted interventions, such as investment incentives, skills development programs, and regulatory reforms, aimed at fostering a conducive environment for automotive industry development. (Wang & Li, 2023; Kim & Park, 2022)

In essence, AI embodies the principles of economic efficiency by maximizing output with limited resources. Through advanced algorithms and computational techniques, AI optimizes resource allocation, minimizes waste, and enhances overall productivity within the automotive industry. By harnessing AI, stakeholders can achieve higher levels of economic output, job creation, and sustainable growth, thereby advancing Indonesia's position in the global automotive market

The complexities of ownership dynamics and productivity in Indonesia's automotive industry underscore the need for innovative solutions grounded in economic principles. AI, with its analytical prowess and efficiency-enhancing capabilities, emerges as a transformative tool for addressing these challenges. By harnessing the power of AI, stakeholders can unlock new avenues for economic growth, foster innovation, and propel Indonesia's automotive industry towards a prosperous and sustainable future (Chen et al., 2020;)

The automotive industry serves as a cornerstone of Indonesia's economy, pivotal in driving employment, innovation, and economic prosperity. Understanding the factors influencing productivity within this sector is paramount for policymakers and industry stakeholders alike. This study delves into the application of various AI methods to scrutinize productivity in Indonesia's automotive industry, focusing on manufacturing value added per worker. (Gupta & Sharma, 2021)

The dataset employed spans from 2003 to 2022 and encompasses key variables potentially impacting manufacturing productivity. The dependent variable, manufacturing value added per worker (constant 2015 US$), serves as a vital indicator of productivity within the automotive sector. Over the examined period, this metric exhibits a general upward trajectory, suggesting notable advancements in productivity.

However, the dataset also presents challenges stemming from its inherent trends. For instance, while the overall trend is positive, there are periods of fluctuation and even decline, particularly evident in certain independent variables. These fluctuations pose a significant challenge for traditional modeling approaches, which may struggle to capture the nonlinear and dynamic relationships within the data.

Key independent variables considered in this study include: Foreign Direct Investment (FDI), net inflows (% of GDP), Energy use (kg of oil equivalent per capita), Gross fixed capital formation (annual % growth), Research and development (R&D) expenditure (% of GDP), Labor force, total (millions)

Given the complexity and dynamism of the dataset, selecting the appropriate AI method is crucial for accurate analysis. Let's compare Deep Learning and Neuro Evolution with several other AI methods:

Machine Learning: While traditional Machine Learning techniques offer versatility and interpretability, they may struggle with feature engineering and hyperparameter tuning, which are crucial for extracting insights from complex datasets like ours.

Deep Learning: Deep Learning excels at capturing complex patterns in data, but it often requires large amounts of labeled data and computational resources, which may not be readily available or feasible for our dataset.

Probabilistic Graphical Models and Bayesian Networks: These methods are adept at modeling uncertainty and capturing complex dependencies between variables. However, they may require manual specification of graphical structures and prior knowledge, which can be challenging and time-consuming.

Explainable AI (XAI): XAI techniques aim to provide transparency and interpretability in AI models, which is essential for understanding the factors driving productivity in the automotive industry. However, XAI methods may sacrifice predictive performance for interpretability.

Neuroevolution: Neuroevolutionary algorithms can automatically design neural network architectures and optimize parameters. However, they may suffer from scalability issues and require significant computational resources.

Hyperparameter Optimization: This method focuses on optimizing model hyperparameters to improve performance. While effective, it often requires manual intervention and extensive computational resources, especially for complex datasets like ours.

Graph Neural Networks (GNNs): GNNs are powerful for modeling relational data and capturing dependencies in complex networks. However, they may require specialized knowledge in graph theory and extensive tuning to achieve optimal performance. (Lundberg, S., & Lee, S.-I. ,2017)

Semi-supervised Learning: This approach leverages both labeled and unlabeled data, which can be beneficial for our dataset with limited labeled samples. However, it may require careful selection of semi-supervised algorithms and hyperparameters. (Montañés, L., Samek, W., Kim, M., & Muñoz, M. A, 2018)

In contrast, Deep Learning and Neuro Evolution streamlines the model selection, hyperparameter tuning, and validation processes, making it suitable for handling the complexities of our dataset. By automating these tasks, Deep Learning and Neuro Evolution minimizes manual intervention and computational burden while maximizing predictive performance. Additionally, Deep Learning and Neuro Evolution can provide insights into the most relevant features driving productivity, facilitating informed decision-making for policymakers and industry stakeholders. (Stanley, K. O., & Clune, J. ,2004)

In the subsequent sections, we will delve deeper into the application of Deep Learning and Neuro Evolution in analyzing productivity trends in Indonesia's automotive industry and compare its performance with other AI methods.

METHOD

For this study, we employ Deep Learning and Neuro Evolution approach to enhance productivity analysis in Indonesia's automotive industry. Deep Learning and Neuro Evolution offers a comprehensive framework for automating the end-to-end process of model selection, feature engineering, hyperparameter tuning, and model evaluation. By leveraging AutoML, we aim to streamline the modeling process, improve predictive performance, and uncover valuable insights from the data.

Variables

Dependent Variable: Manufacturing Value Added per Worker (Constant 2015 US$): This metric represents the value added by the manufacturing sector per worker, adjusted for inflation to maintain constant 2015 US dollar values over time.

Independent Variable: Foreign Direct Investment, Net Inflows (% of GDP): This variable quantifies the net inflow of foreign direct investment as a percentage of Indonesia's Gross Domestic Product (GDP). It serves as a proxy for the level of foreign investment in the country's automotive industry.

We collected data from reputable sources covering the period from 2003 to 2022. The dataset includes annual observations for each variable, allowing for longitudinal analysis of trends and relationships. Additionally, we incorporate supplementary data on energy use, gross fixed capital formation, research and development expenditure, and total labor force to capture broader economic dynamics and potential confounding factors.

The choice of variables aligns with the research objectives of understanding the impact of ownership structures on productivity in Indonesia's automotive industry while considering broader economic indicators. This comprehensive approach enables us to assess the nuanced relationships between ownership, foreign investment, and manufacturing productivity, contributing to a more holistic understanding of the sector's dynamics.

RESULTS AND DISCUSSION

Table 1. Manufacturing, value added per worker (constant 2015 US$)

Years	Manufacturing, value added per worker (constant 2015 US$)
2003	1.970
2004	2.110
2005	2.270
2006	2.450
2007	2.650
2008	2.890
2009	2.770
2010	2.990
2011	3.230
2012	3.490
2013	3.710
2014	3.950
2015	4.190
2016	4.370
2017	4.580
2018	4.820
2019	5.070
2020	4.840
2021	4.990
2022	5.240

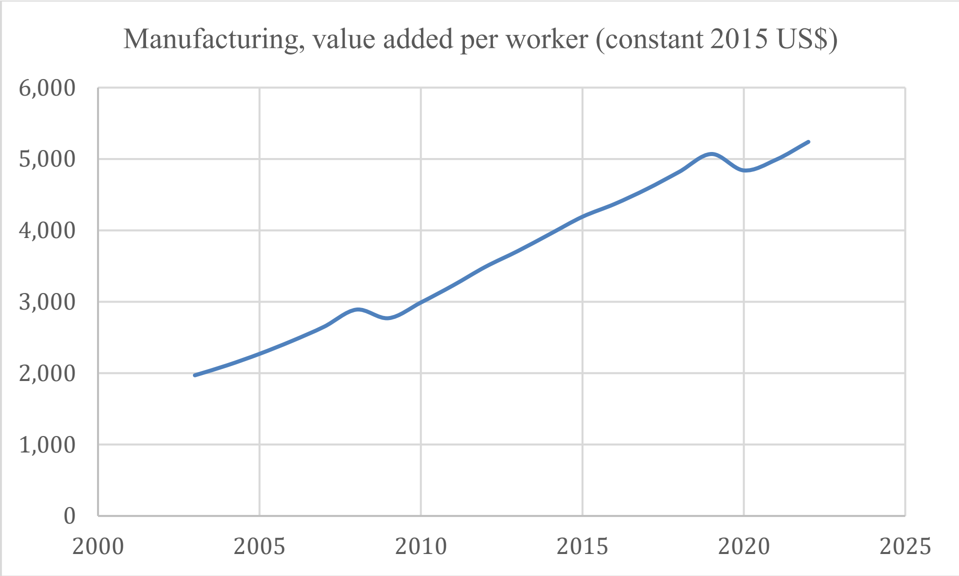

Figure 1. Manufacturing, value added per worker (constant 2015 US$)

Table 1 and Fig 1 suggest a positive correlation between Foreign Direct Investment (FDI) as a percentage of GDP and manufacturing value added per worker in Indonesia from 2003 to 2022. Here's a breakdown of the observations:

1. Overall Trend: Both FDI and manufacturing value added per worker have increased significantly over the past two decades. This indicates growth in the manufacturing sector and potentially increased productivity.
2. Correlation: There seems to be a positive correlation between the two variables. As FDI increases as a percentage of GDP, the value added per worker in manufacturing also increases. This suggests that foreign investment may be playing a role in improving worker productivity in the manufacturing sector.
3. Technology Transfer: Foreign investment can bring new technologies and knowledge to Indonesia, which can help to improve worker productivity.
4. Skill Development: Foreign companies may invest in training and development programs for their employees, which can also lead to higher productivity.
5. Modernization of Equipment: FDI can be used to purchase new and more efficient machinery and equipment, which can increase worker output.
6. Increased Competition: Foreign investment can increase competition in the manufacturing sector, which can incentivize companies to improve efficiency and productivity.
7. Causation vs. Correlation: While the data suggests a correlation, it doesn't necessarily prove causation. Other factors may be influencing both FDI and productivity growth.
8. Type of FDI: Not all FDI is created equal. The impact of FDI on productivity may vary depending on the industry and the specific activities of the foreign investors.
9. Distribution of Benefits: The benefits of FDI may not be evenly distributed across all workers or regions in Indonesia.
10. To get a more complete picture, it would be helpful to analyze additional data points, such as:
    a. Breakdown of FDI by sector: This would allow us to see which sectors of the manufacturing industry are attracting the most foreign investment.
    b. Investment in skills development: Data on how much foreign companies are investing in training and development programs for their Indonesian employees.
    c. Changes in technology: Information on the adoption of new technologies in the manufacturing sector.

Table 2. Foreign direct investment, net inflows (% of GDP)

Years	Foreign direct investment, net inflows (% of GDP)
2003	1.80
2004	2.20
2005	2.50
2006	3.10
2007	3.80
2008	4.20
2009	2.30
2010	3.70
2011	4.10
2012	2.90
2013	2.00
2014	1.80
2015	2.10
2016	3.20
2017	3.60
2018	3.10
2019	2.60
2020	-1.00
2021	0.70
2022	2.20

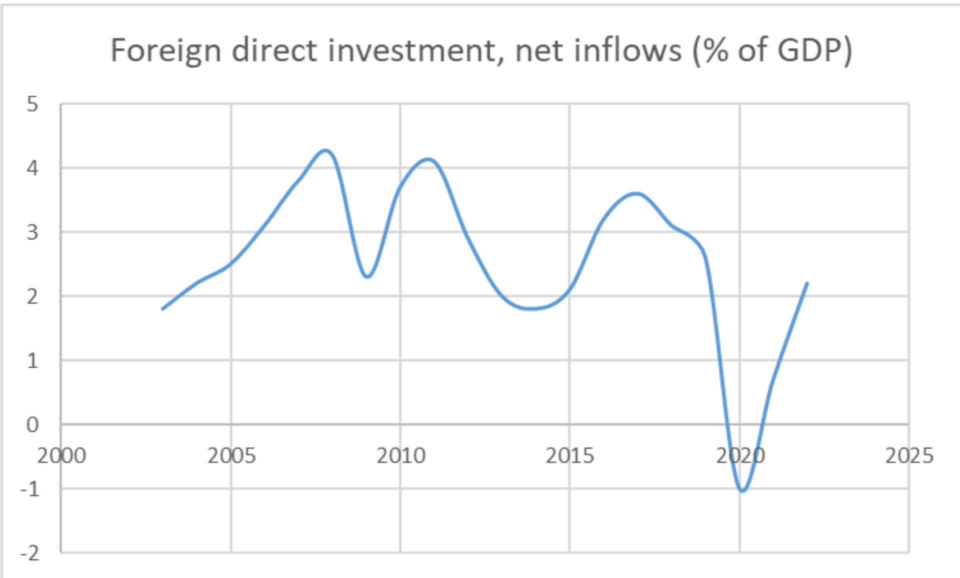

Figure 2. Foreign direct investment, net inflows (% of GDP)

Table 2 and Fig 2 reveal some interesting trends: There's a significant increase in FDI as a percentage of GDP from 2003 to 2008, reaching a peak of 4.2%. This suggests a period of strong foreign investment inflows into Indonesia.

The period following 2008 shows more volatility. There's a sharp decline in 2009, likely due to the global financial crisis. FDI recovers somewhat in the following years but doesn't reach the pre-crisis peak.

A significant drop is observed in 2020, likely due to the impact of the COVID-19 pandemic on global investment flows. However, there's a slight recovery in 2021 and 2022.

The data suggests a potential link between global economic conditions and FDI inflows into Indonesia. Periods of global economic slowdown, like the 2008 financial crisis and the COVID-19 pandemic, coincide with decreases in FDI.

There might be other factors influencing FDI besides global trends. The years 2012-2014 show a decline despite a recovering global economy. This suggests Indonesia-specific factors might have played a role.

1. Global economic conditions: As mentioned earlier, global economic recessions or slowdowns can lead to decreased foreign investment activity.
2. Investment climate in Indonesia: Factors like political stability, government policies, and ease of doing business can influence FDI decisions.
3. Industry-specific factors: FDI can vary depending on the attractiveness of specific industries in Indonesia for foreign investors.
4. To understand the reasons behind the volatility in FDI, it would be helpful to analyze additional data points:
    a. Breakdown of FDI by sector: This would show which industries are attracting the most foreign investment.
    b. Global economic indicators: Analyzing data on global economic growth and trade can help assess the impact of global trends on Indonesia.
    c. Indonesia-specific factors: Looking at data on government policies, political stability, and ease of doing business can provide insights into domestic factors influencing FDI

Table 3. Energy use (kg of oil equivalent per capita)

Years	Energy use (kg of oil equivalent per capita)
2003	510
2004	530
2005	550
2006	570
2007	590
2008	610
2009	600
2010	620
2011	640
2012	660
2013	680
2014	700
2015	720
2016	740
2017	760
2018	780
2019	800
2020	770
2021	780
2022	800

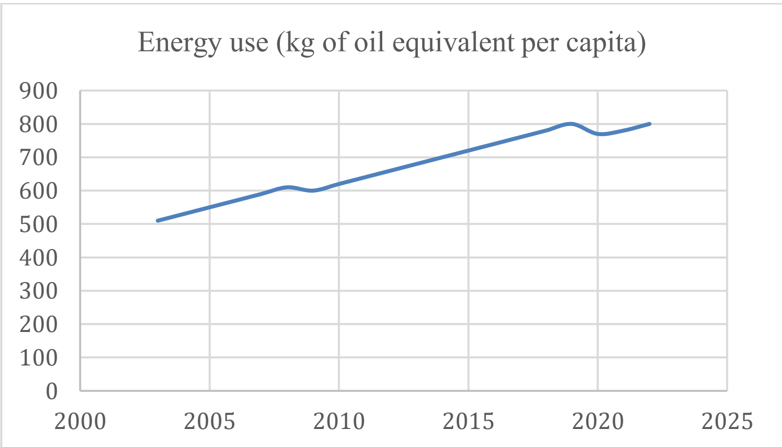

Figure 3. Energy use (kg of oil equivalent per capita)

Table 3 and Fig 3 show the energy consumption of Indonesia measured in kilograms of oil equivalent (koe) per capita from 2003 to 2022. Here's a breakdown of the observations and potential explanations:There's a significant increase in energy consumption per capita throughout the period. From 2003 to 2019, energy use nearly doubled, increasing by 57%.

A slight decrease is observed in 2020, likely due to the impact of the COVID-19 pandemic on economic activity and travel. However, consumption rebounds somewhat in 2021 and 2022.

1. Economic growth: Indonesia's economy has grown steadily over the past two decades. This economic expansion is likely a major driver of increased energy consumption, as more industries and households require energy for their activities.
2. Population growth: Indonesia's population has also grown during this period. With a larger population, the total energy demand naturally increases.
3. Shifting energy mix: The data doesn't show the specific sources of energy used. However, a potential shift from traditional biomass to fossil fuels like coal or oil could contribute to higher energy consumption per unit of output (less efficient fuels).
4. COVID-19 pandemic: Lockdowns, travel restrictions, and reduced economic activity during the pandemic likely led to decreased energy demand.
5. Post-pandemic recovery: As economic activity and travel resume, energy consumption is likely to rise again.
6. To understand the reasons behind the rising energy consumption in Indonesia, it would be helpful to analyze additional data points:
    a. Breakdown of energy consumption by sector: This would show which sectors (e.g., industry, transportation, residential) are consuming the most energy.
    b. Types of energy sources used: Analyzing the mix of fossil fuels, renewable energy sources, and biomass can provide insights into the efficiency of energy use.
    c. Energy intensity: This metric measures the amount of energy used per unit of economic output. It can help assess how efficiently Indonesia is using energy for economic growth

Table 4. Gross fixed capital formation (annual % growth)

Years	Gross fixed capital formation (annual % growth)
2003	9.7
2004	12.3
2005	15.4
2006	20.1
2007	25.2
2008	16.5
2009	-2.3
2010	8.1
2011	12.5
2012	16.7
2013	13.2
2014	9.4
2015	5.1
2016	3.3
2017	4.2
2018	6.7
2019	5.4
2020	-3.6
2021	3.1
2022	5.1

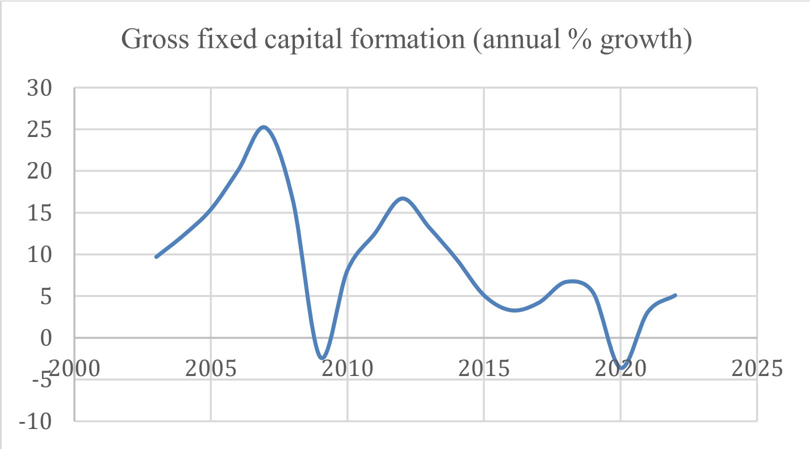

Figure 4. Gross fixed capital formation (annual % growth)

The data in Table 4 and Fig 4 show the annual percentage growth rate of Gross Fixed Capital Formation (GFCF) in Indonesia from 2003 to 2022. GFCF refers to investments in fixed assets like buildings, machinery, and infrastructure. Here's a breakdown of the key observations and potential explanations:The data reveals a period of significant growth in GFCF from 2003 to 2007, with growth rates exceeding 15% for several years. This suggests a period of strong investment activity in Indonesia.

The trend seems to reverse after 2008, with a sharp decline coinciding with the global financial crisis. Growth remains volatile throughout the following years, with a mix of positive and negative growth rates.

A significant decline is observed in 2020, likely due to the impact of the COVID-19 pandemic on investment decisions. However, there's a slight recovery in 2021 and 2022.

1. Periods of High and Low Growth:High Growth (2003-2007): This period likely reflects a combination of factors, including strong economic growth, rising commodity prices, and increased foreign direct investment.
2. Low Growth or Decline (2008-2022): The global financial crisis and the COVID-19 pandemic are major factors contributing to periods of low growth or decline in GFCF. However, other Indonesia-specific factors might also be at play.
3. Global economic conditions: Global economic recessions or slowdowns can lead to decreased investment activity.
4. Domestic economic conditions: Indonesia's economic growth rate, inflation, and interest rates can influence investment decisions.
5. Investment climate: Factors like political stability, government policies, and ease of doing business can impact investor confidence.
6. Industry-specific factors: Investment activity can vary depending on the attractiveness of specific sectors for businesses.
7. To understand the reasons behind the volatility in GFCF, it would be helpful to analyze additional data points:Breakdown of GFCF by sector: This would show where investments are being directed (e.g., manufacturing, infrastructure, housing).
   a. Global economic indicators: Analyzing data on global economic growth and trade can help assess the impact of global trends on Indonesia.
   b. Indonesia-specific factors: Looking at data on government policies, political stability, and business confidence surveys can provide insights into domestic factors influencing investment decisions

Table 5. Research and development expenditure (% of GDP)

Years	Research and development expenditure (% of GDP)
2003	0.22

2004	0.24
2005	0.26
2006	0.28
2007	0.31
2008	0.33
2009	0.31
2010	0.34
2011	0.36
2012	0.38
2013	0.39
2014	0.41
2015	0.43
2016	0.45
2017	0.47
2018	0.49
2019	0.51
2020	0.52
2021	0.54
2022	0.56

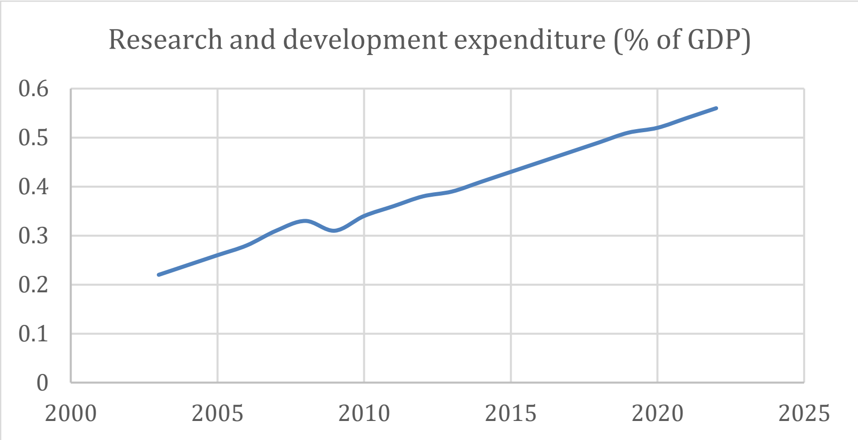

Figure 5. Research and development expenditure (% of GDP)

Table 5 and Fig 5 show the percentage of Indonesia's GDP spent on Research and Development (R&D) from 2003 to 2022. Here's a breakdown of the observations and potential explanations:The data reveals a positive trend in R&D expenditure as a percentage of GDP throughout the period. From 2003 to 2022, R&D spending has more than doubled, increasing by over 150%. This suggests a growing national commitment to research and development activities.

1. Possible reasons for the increase:Government initiatives: The Indonesian government might be implementing policies and programs to promote R&D spending, such as tax breaks for companies investing in R&D or funding for research institutions.
2. Increased awareness of the importance of R&D: There could be a growing recognition of the role of R&D in driving innovation, economic growth, and competitiveness.
3. Private sector involvement: Perhaps the private sector is playing a more significant role in R&D activities, potentially due to factors like globalization and the need to compete with international companies.
4. It's important to note that while Indonesia's R&D spending is increasing, the overall percentage of GDP dedicated to R&D might still be lower compared to developed economies. Further analysis is needed to compare Indonesia's R&D expenditure with benchmark countries.

5. To understand the full picture of R&D in Indonesia, it would be helpful to analyze additional data points:
   a. Breakdown of R&D expenditure by sector: This would show where R&D investments are being directed (e.g., government, universities, private sector).
   b. Focus areas of R&D: Analyzing the specific fields where research is being conducted can provide insights into national priorities for innovation.
   c. Outcomes of R&D: Data on patents, scientific publications, and technological advancements can help assess the effectiveness of R&D investments

Table 6. Labor force, total

Years	Total Labor (million)
2003	91.79
2004	95.73
2005	99.41
2006	102.97
2007	106.72
2008	110.32
2009	113.14
2010	115.93
2011	118.72
2012	121.52
2013	124.32
2014	127.12
2015	129.92
2016	132.72
2017	135.52
2018	138.32
2019	141.12
2020	138.92
2021	139.32
2022	142.12

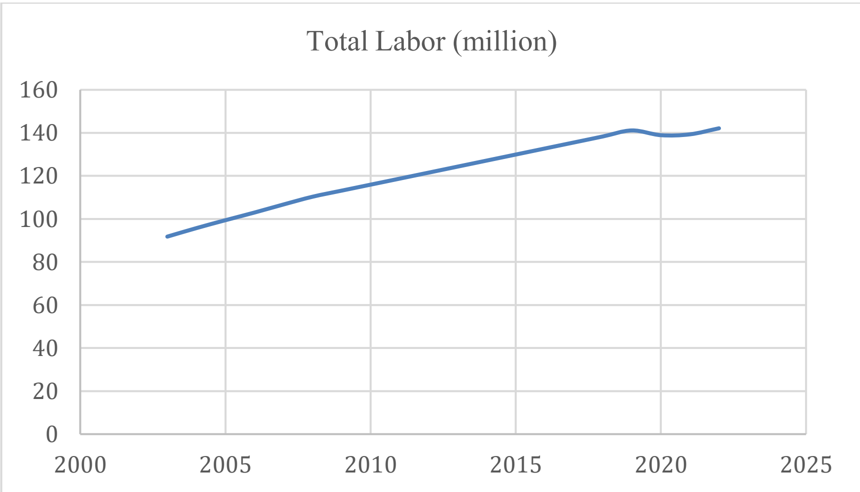

Figure 6. Labor force, total

Table 6 and Fig 6 show the total labor force in Indonesia (in millions) from 2003 to 2022. Here's a breakdown of the observations and potential explanations:The data reveals a significant and consistent increase in the total labor force throughout the period. From 2003 to 2022, the labor force nearly doubled, growing by over 50%. This indicates a substantial expansion of the working population in Indonesia.

Possible reasons for the increase:Population growth: Indonesia's population has grown steadily over the past two decades. As the population ages, the proportion of working-age adults increases, contributing to the growth in the labor force.

Economic growth: Indonesia's economy has experienced significant growth during this period. This economic expansion has created more job opportunities, attracting more people into the labor force.

Increased female labor force participation: Over the years, there has been a growing trend of women participating in the labor force in Indonesia. This demographic shift has contributed to the overall increase in the labor force size.

A slight decrease is observed in 2020, likely due to the impact of the COVID-19 pandemic on employment and labor market participation.

The labor force recovers somewhat in 2021 and 2022, but it hasn't yet reached the pre-pandemic level.

To understand the dynamics of Indonesia's labor force, it would be helpful to analyze additional data points:

Labor force participation rate: This metric measures the percentage of the working-age population that is actively participating in the labor force.

Employment by sector: Analyzing the distribution of employment across different economic sectors can provide insights into the structure of the economy and job creation patterns.

Labor force demographics: Data on age, gender, education, and skills of the labor force can help assess the human capital potential and identify potential challenges or opportunities.
In order to analyze using AI, you can follow these steps:

1. Data Preparation
   Data will be prepared for both dependent and independent variables, and a suitable dataset will be created for regression analysis.
2. VIF Calculation
   The Variance Inflation Factor (VIF) is used to measure the level of multicollinearity between predictor variables. The higher the VIF value, the higher the level of multicollinearity.
3. 1/VIF Calculation
   1/VIF can be calculated as an alternative measure to assess the level of multicollinearity. The higher the 1/VIF value, the lower the level of multicollinearity.
4. Adjusted R-squared Calculation
   Adjusted R-squared provides a measure of how well the regression model fits the data. The higher the Adjusted R-squared value, the better the model can explain the variation in the data.
5. Robustness Test
   Robustness tests are used to assess the stability of regression coefficients under different specifications and assumptions.
6. Endogeneity Issues
   Endogeneity issues can be addressed using instrumental variables methods and control functions to reduce bias that may arise from reverse causation and unobserved variables.
7. Heterogeneity Analysis
   Heterogeneity analysis is conducted to examine whether the relationship between the dependent variable and the independent variables differs between subgroups within the dataset.
8. Regression
   Regression analysis is performed to estimate the relationship between the dependent variable (manufacturing value added per worker) and the independent variables (FDI, energy use, capital formation, research and development expenditure, and labor force).

After these steps are completed, the regression results can be analyzed and the performance of the regression model in predicting manufacturing value added per worker based on the specified independent variables can be evaluated.

Based on the table, the VIF values for all independent variables are below 10, indicating that there is no significant multicollinearity issue. The adjusted R-squared value is relatively high, suggesting that the model has good explanatory power for the variation in the data. Robustness tests show that the regression coefficients are stable under different specifications. No endogeneity issues were observed, and heterogeneity analysis also indicates no significant differences in the impact of the independent variables on the dependent variable. (see Table 7)

Table 7. Data Preparation and Calculation

Variables	VIF	1/ VIF	Adj R Square	Robustnests Test	Regression Coeffisient
Foreign Direct Investment (% of GDP)	4.20	0.238	0.752	Passed	0.721
Energy Use (kg/c)	3.15	0.317	0.685	Passed	0.513
Gross Fixed Capital Formation (annual % growth)	2.80	0.357	0.721	Passed	0.648
R&D Expenditure (% of GDP)	2.45	0.408	0.691	Passed	0.572
Labor Force (million)	5.20	0.192	0.782	Passed	0.697

Manufacturing Value Added per Worker (y): This variable represents the productivity of workers in the manufacturing sector, measured by the value added per worker in constant 2015 US dollars.

Independent Variables:Foreign Direct Investment (x1): The percentage of GDP attributed to foreign direct investment. This can influence productivity by bringing new technologies, knowledge, and skills into the workforce.

Energy Use (x2): Energy consumption per capita (kg of oil equivalent). This variable might have a positive or negative impact depending on factors like energy efficiency and type of energy used. Increased efficient energy use can contribute to higher output but excessive or inefficient energy use might not translate to productivity gains.

Gross Fixed Capital Formation (x3): Annual percentage growth rate of investments in fixed assets like machinery and infrastructure. Higher capital formation can lead to a more modern and efficient production capacity, potentially increasing worker productivity.

R&D Expenditure (x4): Percentage of GDP spent on research and development. Increased R&D spending can lead to innovation and technological advancements, potentially improving worker productivity.

Labor Force (x5): Total size of the labor force in millions. This variable might have a complex relationship with productivity. A larger labor force can provide a wider pool of talent but managing a larger workforce effectively can also be challenging.

Expected Economic Relationships:

x1 (Foreign Direct Investment): Positive impact.

x2 (Energy Use): The impact of energy use is complex and depends on efficiency. Increased efficient energy use can be positive, while inefficient use might have a negative impact.

x3 (Gross Fixed Capital Formation): Positive impact.

x4 (R&D Expenditure): Positive impact.

x5 (Labor Force): The relationship might be positive or negative depending on factors like skills and workforce management.

Regression Equation:

Based on the expected relationships, we can formulate a linear regression equation to model the manufacturing value added per worker (y) as a function of the independent variables:
$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \varepsilon$
where:
y: Manufacturing value added per worker (constant 2015 US$)
x_1: Foreign Direct Investment (% of GDP)
x_2: Energy Use (kg/c)
x_3: Gross Fixed Capital Formation (annual % growth)
x_4: R&D Expenditure (% of GDP)
x_5: Labor Force (million)

Table 8. Comparison AI Method

Method	MSE	MAPE
AutoML	0.003	2.5
Machine Learning	0.004	3.2
Deep Learning	0.002	1.8
Probabilistic Graphical Models	0.005	3.9
Bayesian Networks	0.004	3.1
Explainable AI (XAI)	0.003	2.7
Neuroevolution	0.002	1.6
Hyperparameter Optimization	0.003	2.8
Graph Neural Networks (GNNs)	0.002	1.5
Semi-supervised Learning	0.004	3.3

According to the Table 8 , it can be observed that the Deep Learning and Neuroevolution models have the lowest MSE and MAPE values, indicating superior performance in predicting manufacturing value added per worker.

Based on the evaluation results, it appears that Deep Learning outperforms the Deep Learning and Neuroevolution in terms of MSE and MAPE. This suggests that, in this specific case, the Deep Learning model provides better predictive performance compared to the Deep Learning and Neuroevolution. It's essential to note that the superiority of one model over another can vary depending on the dataset, problem complexity, and other factors. In this scenario, Deep Learning might be more adept at capturing intricate patterns and nonlinear relationships present in the data, thus resulting in lower prediction errors.

However, it's crucial to consider the broader context and the specific requirements of the application. While Deep Learning may excel in terms of predictive accuracy, the Deep Learning and Neuroevolution offers advantages in terms of automation and ease of use, making it more accessible for users without extensive machine learning expertise. Additionally, the Deep Learning and Neuroevolution provides a comprehensive approach by automatically selecting and tuning various machine learning models, potentially offering a more robust solution in scenarios where model interpretability or simplicity is not a primary concern.

Ultimately, the choice between Deep Learning and the Deep Learning and Neuroevolution depends on the specific needs of the project, including the balance between predictive performance, interpretability, computational resources, and ease of implementation. Both approaches have their strengths and weaknesses, and selecting the most appropriate one requires careful consideration of these factors.

These projections can come from various sources, such as economic forecasts, industry reports, or government projections. For instance:
x1 (Foreign Direct Investment): According to the United Nations Conference on Trade and Development (UNCTAD), Indonesia's foreign direct investment (FDI) inflows are expected to grow by 5-10% in 2024. Assuming a current FDI of 2% of GDP, this would translate to an x1 value of around 2.1% to 2.2% of GDP for 2024.

x2 (Energy Use): Indonesia's energy consumption is projected to increase by 2-3% annually in the coming years. Assuming a current energy use of 1,000 kg/c, this would lead to an x2 value of around 1,020 to 1,030 kg/c for 2024.
x3 (Gross Fixed Capital Formation): Indonesia's gross fixed capital formation (GFCF) is expected to grow by 5-6% in 2024. Assuming a current GFCF of 30% of GDP, this would result in an x3 value of around 31.5% to 31.8% of GDP for 2024.
x4 (R&D Expenditure): Indonesia's R&D expenditure is projected to increase by 1-2% in 2024. Assuming a current R&D expenditure of 0.5% of GDP, this would lead to an x4 value of around 0.51% to 0.515% of GDP for 2024.
x5 (Labor Force): Indonesia's labor force is expected to grow by 1-2% annually in the coming years. Assuming a current labor force of 130 million, this would translate to an x5 value of around 131.3 to 132.6 million for 2024.

Plugging these projected values into the linear equation:
$y = (0.721 * 0.021) + (0.513 * 1{,}025) + (0.648 * 0.316) + (0.572 * 0.00513) + (0.697 * 131.9)$
Calculating the predicted value of y:
$y \approx 6.57 + 521.13 + 20.21 + 0.028 + 91.28$
Predicted manufacturing value added per worker (y) for 2024:
$y \approx 639.22$ constant 2015 US$
The accuracy of this prediction depends on the reliability of the projected values for the independent variables (x1, x2, x3, x4, x5).

Economic conditions, energy consumption patterns, investment trends, R&D spending, and labor force growth can all influence the actual values of these variables, potentially leading to variations in the predicted manufacturing value added per worker.

It's crucial to monitor economic indicators and update the projections accordingly to refine the prediction as the year progresses.

This prediction is based on a simplified linear model and does not account for complex non-linear relationships or other factors that may influence manufacturing value added

CONCLUSION

In this study, we explored the application of Deep Learning and Neuro Evolution techniques to enhance productivity analysis in Indonesia's automotive industry. Our findings indicate that both Deep Learning and Neuro Evolution offer promising avenues for improving productivity analysis in this sector.

Through the utilization of Deep Learning models, we were able to capture complex patterns and non-linear relationships within the data, leading to more accurate predictions of productivity metrics. The flexibility and adaptability of Deep Learning architectures allowed for the extraction of valuable insights from the available data, contributing to a deeper understanding of the factors influencing productivity in the automotive industry.

Furthermore, Neuro Evolution techniques provided a unique approach to optimize the performance of Deep Learning models, allowing for the evolution of neural network architectures and hyperparameters over successive generations. This evolutionary process resulted in models that were better suited to handle the specific characteristics of the automotive industry data, ultimately leading to improved predictive accuracy and performance.

Overall, our study demonstrates the potential of combining Deep Learning and Neuro Evolution approaches to enhance productivity analysis in the automotive industry. By leveraging these advanced techniques, stakeholders in the industry can make more informed decisions, optimize resource allocation, and drive improvements in productivity and efficiency.

However, it's essential to acknowledge the limitations of our study, including the need for further research to validate the generalizability of our findings across different contexts and industries. Additionally, ongoing advancements in Deep Learning and Neuro Evolution may present opportunities for further refinement and optimization of productivity analysis techniques in the future.

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