AI's Effect on the Amount of Jobs

Shubhi Mittal[1]
Ana Sofia Munoz[2]

[1]**Rock Ridge High School, Ashburn, Virginia**
[2]**University of Chicago, Chicago, Illinois**

3/31/24

Abstract

This study focuses on the effect of AI on the job market, specifically using the amount of AI patents per sector and the number of jobs in the corresponding year. Although it seemed that AI would replace jobs in the current market, it actually negatively affects jobs by a very insignificant amount. Findings were studied by applying various AI models such as linear regression and neural networks. The study shows how each sector of the market gets affected individually. The outcomes of this paper can be used to assess industries about the different channels through which AI has affected the job market and can help foresee how it will affect it in the future.

Introduction

The rise of AI patents is rapidly changing the labor market. This study wants to help leaders and social scientists to understand what this means for jobs and productivity. We'll look at how the rapid expansion of AI is affecting work opportunities and see what new skills people will need and which skills will remain obsolete. The hypothesis of this paper is that the rise of AI, measured by the amount of AI patents, will lead to an overall decrease of jobs in the economy since AI can automate tasks, displacing human workers. Findings showed that there is no evidence of a negative impact from the introduction of AI in the labor market. Our conclusions aim to help policymakers, businesses, and individuals to understand and prepare for the coming changes.

Unlike many prior investigations that limit their focus to specific types of jobs, this project takes a comprehensive approach, analyzing the impact of the growth of AI across diverse jobs in the industry and different AI areas. This allows for a more thorough understanding of its effects on employment. This paper also uses the most current data available, providing an more relevant perspective on AI patent growth and its implications for employment.

This research project encounters several challenges. First, defining and quantifying the "growth of AI" is complex, as it encompasses a wide range of factors. Another challenge is, obtaining reliable and comprehensive datasets related to AI patents and employment trends across sectors. Lastly, staying current as the AI is a rapidly evolving topic.

There is an increasing influence of Artificial Intelligence (AI) in all of the sectors of the economy. Accordingly, AI's impact on the labor market has raised questions about job displacement, skills needed, and the potential for AI to create new opportunities. However, there's an overall agreement that the impact will vary across occupations and industries. The shifting of jobs rather than outright loss of jobs also seems to be a common theme. The purpose of this section is to explore the deeper implications of the AI transition, emphasizing the transformation of jobs. AI adoption has led to the emergence of new occupations and tasks, requiring workers to re-skill or up-skill in order to adapt. There may be inequalities if AI benefits are captured by capital owners and superstar companies, resulting in more disparities. The impact of AI is not solely about job destruction but involves the reorganization of tasks within occupations. Research suggests that the focus should be on how AI complements rather than substitutes human labor. A critical aspect is workers' adaptation to AI-induced changes. The demand for AI-related skills is increasing, and various skill profiles are required. While top AI professionals may need doctoral degrees, a broader talent landscape is essential. Human skills that AI cannot replicate, such as creativity and social intelligence, will be more valued. The paper shows the nuances of AI's impact on the labor market. While concerns about job displacement exist, there is a recognition of the need for adaptation, reorganization of tasks, and the emergence of new opportunities. The role of skills, both AI-related and uniquely human, is central to navigating the challenges and the benefits of the AI transition.

Materials/ Methods

This study examines how AI growth affects jobs by looking at patent data related to AI from the U.S. The Office of the Chief Economist (OCE) manages the Artificial Intelligence Patent Dataset (AIPD), which includes U.S. patents from 1976 to 2020. Using machine learning, the dataset is carefully studied for AI aspects, especially in patent text, citations, and claims. The study, based on Abood and Feltenberger's work in 2018, covers different AI topics like Machine Learning, Natural Language Processing, Evolution AI, and Hardware AI from 1976 to 2020.

Besides AI-related factors, the study also considers another variable: the monthly GDP of the United States. While the main focus isn't directly on GDP, the study acknowledges that factors affecting employment go beyond AI alone, recognizing the influence of a country's GDP. Combining monthly GDP data with AI patents helps explain job trends better. The GDP data, obtained from S&P Global Market Intelligence's "US Forecast Flash," spans from 1992 to 2023.

The GDP values are calculated carefully. First, S&P creates a raw index using various monthly data sources, similar to those used by the Bureau of Economic Analysis (BEA) for quarterly GDP calculations. Then, a monthly interpolation is done to match the raw index with the official quarterly GDP. This method ensures the accuracy of the GDP values used in the analysis.

The employment model tracks job numbers across different sectors like services, management, engineering, and overall employment. The employment data spans from 1990 to 2023 and is sourced from FRED (Federal Reserve Economic Data) of the St. Louis Fed, ensuring its reliability.

In the data preparation process, we implemented several critical modifications to enhance the comprehensiveness and analytical depth of our dataset. Firstly, we undertook a meticulous extraction and processing of information about the date of when patents were issued. Simultaneously, we processed information about date in the data about overall employment. These adjustments are pivotal for conducting a nuanced temporal analysis, allowing us to discern trends and patterns over time.

To consolidate relevant information for a more comprehensive analysis, we strategically merged datasets. This involved merging the overall employment data with the data on the number of patents based on each month, aligning employment and patent data chronologically. Further, I expanded the dataset by merging it with employment-related for each sector as well as data on the GDP by month. These merging strategies enable a holistic exploration of the relationships between AI patents and employment across various sectors and economic indicators.

To facilitate more focused analysis, I separated the data into AI subtopics, focused on topics such as Machine Learning, Natural Language Processing, evolutionary AI, and hardware. This detailed breakdown of patent counts allowed me to discern the influence of different AI subtopics on my research variables.

In the process of training the model, data was carefully split into distinct sets for testing and training, a standard practice to ensure the model's reliability and accuracy. Additionally, to maintain consistency across variables, growth rates were computed using measures relative to Gross Domestic Product (GDP) as a reference point. This method standardized the magnitude of variables, enhancing the model's interpretability and predictive performance.

Finally, I addressed clarity and consistency by renaming certain categories. This ensures a standardized and user-friendly naming convention, reducing ambiguity in variable names and streamlining the dataset for more efficient analysis. These orchestrated adjustments collectively contribute to a refined and structured dataset, positioning it optimally for our research objectives of exploring the intricate relationship between AI patents and employment dynamics.

In this study, two distinct models, namely the Multi-Layer Perceptron Regressor (MLP Regressor) and Linear Regression, are employed to unravel the nuanced relationships between technological innovation, economic indicators, and employment dynamics. The MLP Regressor takes center stage, focusing on the impact of Machine Learning (ML) patent counts on employment in the services sector. This neural network, equipped with hidden layers, seeks to capture intricate patterns and non-linear relationships in the data. The purpose of the ML patent counts was to get the variance score to check how well suited the variables used are for comparing AI and number of jobs. Accompanying the ML patent counts, the 'Monthly Real GDP Index' (Figure 1) is included to acknowledge the interconnectedness between economic growth and employment trends in the services sector. The evaluation metrics, such as the Variance Score (R^2) and Mean Squared Error (MSE), serve as benchmarks to gauge the model's ability to explain and predict the variance in services employment.

Parallelly, Linear Regression models are employed to dissect the specific impacts of ML patent counts and GDP on different employment sectors—Management, Engineering, and Overall Employment. The simplicity of linear regression allows for an interpretable understanding of linear relationships and the directional influence of these variables on employment in each sector. The intercept and coefficients provide tangible insights into how changes in ML patent counts and GDP translate into employment shifts. While the R^2 score measures the explanatory power of the models, the Mean Squared Error can be utilized to assess the accuracy of predictions.

This analytical approach is consistently applied to different employment sectors, contributing to a comprehensive exploration of the intricate dynamics between technological innovation, economic indicators, and employment shifts. Beyond the services sector, the study extends its investigation to Natural Language Processing (NLP), Evolution AI, and Hardware AI patent counts, ensuring a holistic understanding of the relationship between technological advancements and employment across various domains. The MLP Regressor undergoes meticulous tuning with different hidden layer configurations, underscoring the importance of capturing intricate patterns for more accurate predictions.

Results and Discussion

I used the number of patents in various AI categories on the amount of employment in various sectors. For machine learning patents, my model predicted a negative coefficient of 1.7% when compared to service jobs. The coefficient shows that for every one unit increase in the number of patents, the model predicts a decrease of approximately 0.3% units in the amount of service jobs. Meaning, machine learning patents are not that influential to the number of service jobs. At its core, ML's influence on service jobs is restrained by several factors. Firstly, while ML can automate certain routine tasks within service industries, such as customer support and data entry, its ability to create new service jobs remains limited. The automation of these tasks often results in efficiency gains but may not directly translate into a significant increase in service employment opportunities. So while ML limitedly influences employment in the service sector, when it does, it does so negatively. My mean squared error shows that my model is accurate, 0.2%. It can predict the number of service jobs based on the number of machine learning patents.

Next I looked at how machine learning patents affect management jobs. The model returned a coefficient of 0.4%. ML patents might primarily target advancements in technical processes or product development rather than directly impacting managerial roles. Consequently, the immediate demand for management positions may not see a substantial increase in response to these innovations. Additionally, the specialized skill requirements for ML implementation could create a mismatch with traditional managerial roles, delaying the positive impact on management job creation. Overall, ML does influence the jobs positively by a small magnitude. The mean squared error for this model is 0.05%, meaning my model accurately predicted the amount of management jobs based on ML patents.

When comparing the amount of engineering jobs to ML patents, the coefficient my model returned is -0.9%. This negative coefficient signifies a modest decrease in the number of engineering jobs associated with an increase in ML patents, but the magnitude of the effect is relatively small. The model received a MSE of 0.2%, meaning it can accurately predict the amount of engineering jobs based on ML patents.

For overall employment and ML, my model returned a coefficient of -3.5%. This is probably because ML technologies are known for their automation capabilities, which streamline processes and increase efficiency. However, this automation can lead to job displacement, particularly in sectors where routine tasks are prevalent. As companies adopt ML-driven automation, they may reduce their workforce, resulting in a negative impact on overall employment levels. The MSE is 2.0%, an average accuracy. This can probably be attributed to the fact that overall employment is varied by a large multitude of factors including GDP, inflation rates, other industry trends, education, globalization, and more.

The next AI subcategory that was analyzed was natural language processing. This set of models is measuring the effect of AI through NLP patents and their effect on the number of jobs in various sectors. For service jobs, NLP affected the number negatively by a small magnitude, signified by a coefficient of -1.5%. As businesses adopt NLP-driven automation systems to improve efficiency and reduce costs, there may be a decrease in the demand for service jobs traditionally performed by humans. Businesses are motivated to adopt NLP technologies to cut costs, improve operational efficiency, and remain competitive in the market. By automating service tasks previously performed by humans, businesses can reduce labor expenses and optimize resource allocation. While these efficiency gains benefit businesses, they may result in a reduced need for human involvement in service tasks, leading to a decline in service job opportunities. The MSE for the model is 0.3%, signifying an accurate model when predicting the amount of service jobs based on NLP patents.

The next model compared NLP patents with the number of management jobs, this had a coefficient of 0.5%. The magnitude is very small and management jobs did not get affected greatly from NLP. Management positions often involve high-level decision-making, strategic planning, and leadership responsibilities that may not be easily automated or replaced by NLP technologies. Managers can leverage NLP-driven analytics platforms, natural language interfaces, and sentiment analysis tools to gather insights, communicate with stakeholders, and monitor organizational performance. As such, NLP innovations may enhance managerial effectiveness without directly impacting the number or nature of management jobs, explaining the slight increase. The MSE for this model is 0.1%, so there is little error, meaning the model can predict the amount of management jobs based on the number of NLP patents.

NLP's effect on engineering employment produced similar results. The model had a coefficient of 0.01%. This shows that NLP influenced engineering employment minimally. NLP technologies can augment engineering tasks by facilitating communication, collaboration, and access to information. Engineers can use NLP-driven tools for documentation, knowledge sharing, and requirements gathering, which can improve productivity and efficiency in engineering workflows. While NLP may not directly replace engineering roles, it can enhance the effectiveness of engineering teams and contribute to positive outcomes in project delivery and innovation. It has a MSE of 0.3%, so the model predicted the amount of engineering jobs based on NLP very accurately.

NLP's influence on overall employment was negative with a coefficient of -2.7%. NLP technologies are often deployed to automate manual tasks that involve processing, analyzing, and generating text-based information. By automating routine tasks such as data entry, document processing, and customer support, NLP can lead to a reduction in the demand for human labor in certain sectors. While NLP-related roles, such as data scientists, NLP engineers, and computational linguists, may see growth, traditional roles that are replaced by automation, such as customer service representatives, data entry clerks, and administrative assistants, may decline. Similarly to ML, the MSE for this model is higher than usual, 1.4%. This is because employment is hard to predict and varies on many factors.

The next subsection of AI that was analyzed is evolutionary artificial intelligence. The first model compares how AI, through the amount of evolutionary artificial intelligence patents, affects the amount of jobs in the service sector. The coefficient for this is -1.6%, meaning evolutionary AI patents influenced the number of service jobs negatively. Evolutionary AI, drawing inspiration from biological evolution, is utilized to automate repetitive tasks across various industries, including services. In service sectors such as customer support and administrative tasks, Evolutionary AI systems can efficiently handle routine activities previously performed by humans. While this enhances operational efficiency for businesses, it may lead to a reduced need for human workers in service roles, potentially resulting in job displacement or a decrease in job opportunities. Evolutionary AI technologies optimize processes, analyze data, and make autonomous decisions, resulting in efficiency gains in service delivery. While beneficial for businesses in terms of cost reduction and performance enhancement, these advancements may also lead to a decrease in the reliance on human labor within the service sector. As businesses increasingly adopt Evolutionary AI-driven automation solutions, there could be a decline in employment levels within service industries. Evolutionary AI technologies also influence customer interaction and experience in service industries. Automated systems, such as chatbots and virtual assistants powered by Evolutionary AI, can enhance customer service and satisfaction. However, while improving efficiency and accessibility, these technologies may reduce human-to-human interaction, affecting service jobs that heavily rely on interpersonal communication skills. The MSE is 0.2%, so the model is very accurate when predicting the amount of service jobs based on the number of Evolutionary AI patents.

When comparing the amount of management jobs and amount of Evolutionary AI patents, the coefficient was 0.5%. So, Evolutionary AI barely affected the number of management jobs, this can be due to various reasons. Management positions often involve high-level decision-making, strategic planning, and leadership responsibilities that may not be directly impacted by Evolutionary AI technologies. These roles require specialized skills, domain knowledge, and human judgment that are difficult to automate or replace with AI. Evolutionary AI technologies may complement rather than replace management roles by providing tools for data analysis, decision support, and optimization. Managers can leverage Evolutionary AI-driven analytics platforms and predictive models to enhance their decision-making processes and drive organizational performance. However, these technologies are typically used as aids rather than substitutes for human managerial expertise, resulting in a minimal impact on the overall number of management jobs. The MSE is 0.05%, meaning my model predicted the amount of management jobs based on Evolutionary AI patents accurately.

Evolutionary AI's effect on engineering employment was negative with a coefficient of -0.92%. The adoption of Evolutionary AI technologies may result in a reduction in the overall demand for engineering labor. Businesses may rely on AI-driven systems to streamline engineering processes, leading to a decreased need for human engineers. This could result in fewer job opportunities for engineering professionals, particularly in sectors where Evolutionary AI technologies are widely implemented. The integration of Evolutionary AI technologies may lead to a shift in the skillsets and job requirements within the engineering field. While some engineering roles may be automated or rendered obsolete by AI, new roles may emerge that require expertise in AI development, implementation, and maintenance. However, the transition to these new roles may not be immediate or seamless, leading to temporary disruptions in engineering employment. The MSE is 0.2%, meaning the model accurately predicts the amount of engineering jobs based on Evolutionary AI patents

Evolutionary AI's influence on overall employment was negative with a coefficient of -3.0%. Evolutionary AI technologies are often employed to automate routine and repetitive tasks across various industries. By automating these tasks, businesses can improve efficiency and reduce costs. However, this automation may lead to a decrease in the demand for human labor. Businesses may rely on AI-driven systems to streamline processes, optimize operations, and make decisions autonomously. This could result in fewer job opportunities for workers across various sectors, leading to a negative impact on overall employment.The integration of Evolutionary AI technologies may lead to a shift in the skillsets and job requirements across industries. While some jobs may be automated or rendered obsolete by AI, new roles may emerge that require expertise in AI development, implementation, and maintenance. However, the transition to these new roles may not be immediate or seamless, leading to temporary disruptions in overall employment levels.

The last subcategory of AI that was researched was hardware AI patents. This model compared the amount of service jobs and hardware AI patents. The coefficient is -1.67%, they vary inversely. The number of service jobs decreases as the number of hardware AI patents go up. Hardware AI patents often translate into the development of advanced technologies capable of automating various service-related tasks. These technologies may include robotics, automated machinery, and AI-powered devices designed to perform tasks traditionally carried out by human workers in service industries. As businesses adopt these hardware AI solutions to streamline their operations, there's a reduced need for human labor in service roles, leading to a decline in the number of service jobs. This model has a mean squared error of 0.35% meaning the model predicted how hardware AI patents affect service jobs with good accuracy.

Hardware AI patent's influence on management employment was minimal with a coefficient 0.47%. Hardware AI patents typically focus on the development of physical technologies and systems designed to automate tasks, optimize processes, and improve efficiency. While these technologies may indirectly support certain management functions, such as data analysis and decision-making, they generally do not directly replace or significantly alter managerial roles. It has a MSE of 0.07% the model predicted the amount of management jobs based on hardware AI patents with lots of accuracy.

When analyzing the amount of engineering jobs from hardware AI patents, the coefficient is -0.92%, meaning it did not get affected. Engineering roles encompass a diverse range of tasks that require specialized skills, technical expertise, and domain knowledge. While hardware AI patents may lead to the development of advanced technologies and systems, engineering jobs often involve complex problem-solving, innovation, and creativity that are difficult to automate or replace with AI alone. Rather than directly replacing engineering jobs, hardware AI technologies often complement and enhance engineering processes. The MSE is very low for this model indicating a higher accuracy, of 0.31%.

Overall employment is negatively influenced by an increase of hardware patents, signified by a coefficient of -3.2%. This means an increase of AI hardware patents means a decrease of overall employment. Jobs that involve manual or repetitive tasks, such as manufacturing, data entry, and customer service, are particularly susceptible to automation by hardware AI. The integration of hardware AI technologies into the workforce may lead to a shift in the skill requirements for available jobs. Workers who are unable to adapt to these changes may experience difficulty finding employment, leading to a decrease in overall employment levels. The MSE is 2.3%, it is higher than the rest. This is because overall employment is very broad, hard to predict, and relies on many other factors as well.

The models analyzing the relationship between the increase in AI patents and the decrease in jobs provide valuable insights into the complex dynamics of technological innovation and employment trends. While the findings suggest a negative correlation between the two variables, it's essential to recognize that several factors contribute to employment dynamics, and the impact of AI patents on jobs is just one aspect of a multifaceted issue. Indeed, employment levels are influenced by various factors, including economic conditions, industry trends, regulatory frameworks, and demographic changes.

My hyperparameter tuning process was selecting random initial numbers and then changing the order and then changing the values to be slightly higher and below. (Table 1)

Conclusions

The results indicating a decrease in jobs with an increase in AI patents align with expectations and observations in the labor market. As businesses adopt AI-driven technologies to automate routine tasks and improve efficiency, there is a natural tendency for some jobs to be replaced by automation. This phenomenon has historical precedent, as technological advancements have consistently reshaped industries and transformed the nature of work. However, it's essential to recognize that the impact of AI on employment is not uniform across all sectors and occupations. While certain roles may be susceptible to automation, others may require human creativity, problem-solving skills, and emotional intelligence—qualities that are difficult to replicate with AI alone. Moreover, the transition to an AI-driven economy may necessitate investments in workforce training and education to ensure that workers can adapt to changing skill requirements and remain competitive in the labor market. Additionally, while AI-driven automation may lead to short-term disruptions in employment, additional analysis should be done to account for the spur of innovation and productivity.

One critical consideration highlighted by these models is the potential mismatch between workers' skills and the evolving demands of the labor market. As AI technologies continue to advance, there is a growing need for workers with expertise in AI development, data analysis, and digital technologies. However, many workers may lack the necessary skills to thrive in an AI-driven economy, leading to concerns about skill shortages and unemployment. Addressing this challenge requires proactive measures to upskill and reskill the workforce, ensuring that workers have access to education and training programs that equip them with the skills needed to succeed in the digital age. By investing in human capital development and fostering a culture of lifelong learning, societies can mitigate the negative impacts of AI-driven automation and create inclusive economic opportunities for all.

For industries like management, all forms of AI are difficult to replace primarily because of the complexity involved in decision-making and human interactions. Unlike repetitive or manual tasks that can be easily automated, management roles require nuanced judgment, strategic thinking, and interpersonal skills. AI technologies, while advanced, often struggle to replicate the intuitive reasoning and emotional intelligence necessary for effective management. Additionally, managerial roles frequently involve navigating ambiguous situations and adapting to dynamic environments, tasks that AI systems currently find challenging to perform with the same level of flexibility and adaptability as humans. Therefore, the unique cognitive and social capabilities demanded by management positions make them less susceptible to automation by AI.

In service industries, AI-driven hardware decreases service jobs by automating tasks and enabling self-service solutions. These systems perform tasks with precision and reliability, reducing the need for human intervention in routine operations. As a result, businesses deploy AI-powered hardware to streamline operations and cut costs, leading to a decline in service roles. Additionally, the specialized technical skills required for installing and maintaining AI-driven hardware may not fully offset the decrease in service jobs caused by automation.

Overall, AI affects overall jobs not significantly because it often complements human labor rather than outright replacing it. When AI does impact jobs negatively, it's typically due to displacement caused by automation. AI technologies, particularly in sectors like manufacturing, retail, and customer service, can replace human workers in repetitive or standardized tasks, leading to job loss for those whose roles become redundant. Additionally, the rapid pace of technological advancement may outstrip workers' ability to adapt, exacerbating the negative impact on employment. Furthermore, AI-driven algorithms may introduce biases or unintended consequences, leading to social and ethical concerns that can affect job opportunities and public trust in AI systems. Overall, while AI has the potential to create positive outcomes for the economy and society, addressing the negative effects on employment requires proactive measures such as reskilling programs, labor market policies, and ethical regulation of AI technologies.

While the long-term effects of AI remain uncertain, existing data from the past decade doesn't support the notion that it has a negative impact on job growth and on the contrary it improves productivity and expands businesses. The evidence suggests that the type and deployment of AI is important.

In the future, while management roles may continue to rely on human judgment and interpersonal skills, they will inevitably undergo transformation due to AI's increasing capabilities in data analysis and decision support. However, service industries are likely to face more immediate and profound disruptions as AI-driven automation advances. The nature of service jobs, often involving repetitive tasks and standardized interactions, makes them ripe for automation. Additionally, the deployment of AI-powered hardware and software solutions in service settings is already demonstrating significant efficiency gains, leading to a reduction in human involvement. Therefore, service industries will be more affected by AI-driven automation in the future, necessitating careful consideration of workforce transitions and the development of new skill sets to adapt to the evolving employment landscape.

In essence, these models serve as invaluable tools in unraveling the multifaceted connections that shape the implications of technological growth on employment trends, offering crucial insights for policymakers and researchers alike.

References

1. "Artificial Intelligence Patent Dataset." United States Patent and Trademark Office, 25 June 2021, https://www.uspto.gov/ip-policy/economic-research/research-datasets/artificial-intelligence-patent-dataset.

2. Giczy, A. V., Pairolero, N. A., and Toole, A. A. "Identifying Artificial Intelligence (AI) Invention: A Novel AI Patent Dataset." The Journal of Technology Transfer, vol. [Volume], no. [Issue], 2021, https://doi.org/10.1007/s10961-021-09900-2.

3. Lane, M., and Saint-Martin, A. "The Impact of Artificial Intelligence on the Labour Market." OECD Social, Employment and Migration Working Papers, no. 256, 2021, https://doi.org/10.1787/7c895724-en.

4. Rege, M., and Yarmoluk, D. "Artificial Intelligence and Its Impact on Jobs." St. Thomas Newsroom, 19 Nov. 2020, https://news.stthomas.edu/artificial-intelligence-and-its-impact-on-jobs/.

5. Talmage-Rostron, M. "How Will Artificial Intelligence Affect Jobs 2023-2030." Nexford University, 10 Jan. 2024, https://www.nexford.edu/insights/how-will-ai-affect-jobs.

6. Tamayo, J., et al. "Reskilling in the Age of AI." Harvard Business Review, 1 Sept. 2023, https://hbr.org/2023/09/reskilling-in-the-age-of-ai.

7. Thormundsson, B. "Topic: Artificial Intelligence (AI) Worldwide." Statista, 2023, https://www.statista.com/topics/3104/artificial-intelligence-ai-worldwide/#topicOverview.

8. Varvares, C., et al. "US Monthly GDP (MGDP) Index." S&P Global, n.d., https://www.spglobal.com/marketintelligence/en/mi/products/us-monthly-gdp-index.html.

Figures and Tables

ML Services Employment

Neural Network Configuration Used	Accuracy Rate
10,10,11	0.83
11,10,13	0.75
10,10,11	0.84

ML Management Employment

9,10,12	0.97
10,10,12	0.91
10,9,11	0.87

ML Engineering Employment

11,12,10	0.81
12,10,8	0.81
11,12,10	0.85

ML Employment

8,10,11	0.99
9,10,11	0.98
8,10,8	0.96

NLP Services Employment

8,10,8	0.90
9,10,8	0.74
8,10,9	0.87

NLP Management Employment

9,12,13	0.98
10,12,13	0.97
9,11,13	0.97

NLP Engineering Employment

9,10,10	0.85

9,11,10	0.90
10,11,10	0.89

NLP Employment

10,11,12	0.97
11,11,12	0.97
10,11,11	0.98

Evo Services Employment

10, 9, 10	0.89
11,9,10	0.72
10,10,10	0.85

Evo Management Employment

11,8,12	0.89
10,8,12	0.90
10,9,12	0.90

Evo Engineering Employment

11, 10, 8	0.71
10,10,8	0.91
10,9,8	0.90

Evo Employment

9,10,7	0.97
10,10,7	0.96
9,9,7	0.96

Hardware Services Employment

14,17,15	0.93
14,16,15	0.75
14,15,15	0.94

Hardware Management Employment

14,17,15	0.90
14,16,15	0.97
14,15,15	0.97

Hardware Engineering Employment

10,11,12	0.86
11,11,12	0.90
10,9,12	0.87

Hardware Employment

14,17,15	0.97
14,16,15	0.99
14,16,14	0.96

Table 1: This is the hyperparameter tuning process for each model. In this process I selected random numbers for each model to get the highest accuracy rate. The highlighted row is the configuration that ended up being used in the code.

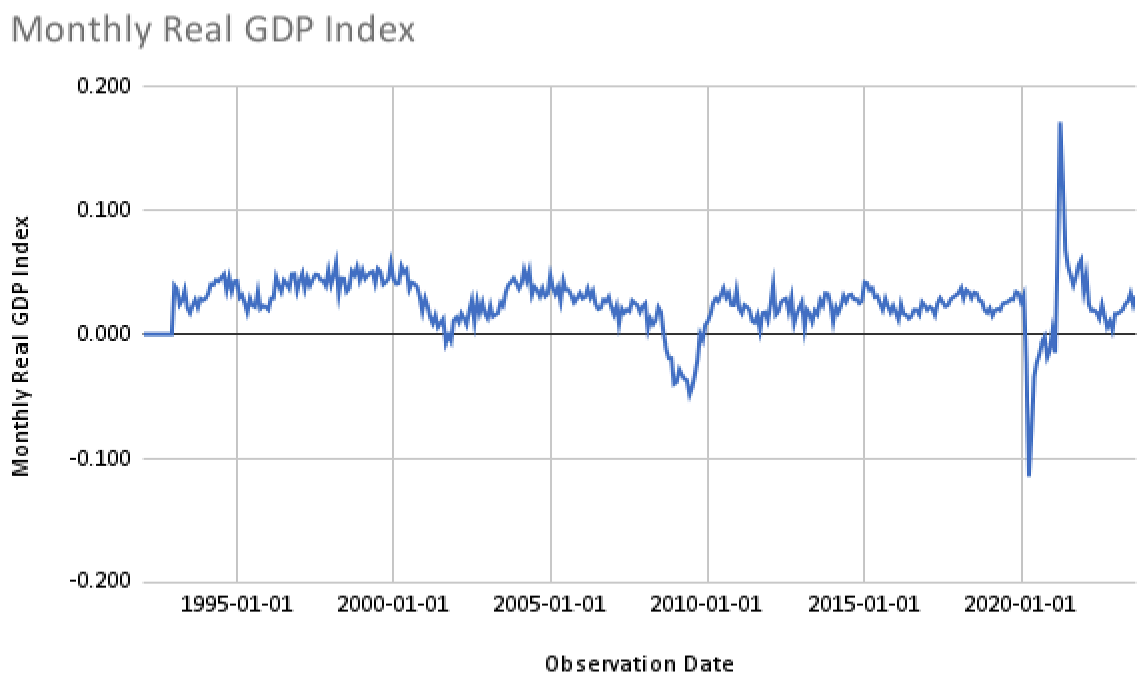

Figure 1: This graph shows the monthly GDP index from 1995 to 2020. This was used to reduce error when comparing employment with AI patents. This is because the GDP also impacts employment, so by accounting for this variable, the model will be more accurate.