Macroeconomic Parameter Prediction: Leveraging Recurrent Neural Networks for US CPI Forecasting

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1 Introduction

Inflation is the percentage rate, typically measured on an annual basis, of the continuing rise in the general price level of goods and services within an economy. The inflation rate also reflects the percentage by which the domestic currency has weakened.

Inflation is one of the most important economic variables to determine the current state of an economy. Too high and purchasing power falls and saving and investment are discouraged. This weakening of the domestic currency can also decrease global competitiveness with exports since domestically produced goods are now more expensive for foreign buyers.

Yet if inflation is too low, it signals that there is a low demand for goods and services in the economy - this can lead to an economic slowdown or even a recession. There is also a lower return on investments for savers, and this lower demand for goods and services can lead to lower profits and job losses for some industries, especially those with small profit margins such as restaurants and other small businesses.

The Consumer Price Index is an inflation statistic reported by the Bureau of Labour Statistics [1]. It represents a weighted basket of goods containing approximately 700 goods and services most bought by the average household.

Forecasting inflation is very important, and most investment banks, as well as government organisations such as the International Monetary Fund, take it upon themselves to provide inflation forecasts for their clients and the general public [2]. For investment banks, understanding inflation trends helps them to make more informed decisions regarding risk management and asset allocation, and the investment strategies they recommend to their clients.

Various methods have been developed and used over time to improve forecasting accuracy, and the field continues to evolve in response to new technological advancements and economic challenges. In recent years there has been an increase in interest in using neural networks for economic forecasting, due to their potential to capture complex relationships between variables [3–5]. This capability allows them to potentially provide more accurate and robust forecasts.

Government organisations, such as central banks, rely on inflation forecasts to determine the extent of the fiscal and monetary policies they will implement to promote economic growth and stability.

For the general public, accurate inflation forecasts can help individuals and business budget more accurately, to anticipate future price increases of goods and services, and to stay informed, and make better financial decisions.

The primary research question that this study will address is twofold. Firstly, the aim is to identify the strongest economic determinants of the US Consumer

Price Index (CPI), the primary measure of inflation in the United States. A thorough understanding of the determinants is crucial in providing a solid foundation for accurate and reliable inflation forecasts. Secondly, the goal is to develop an LSTM neural network model that utilises these identified determinants to forecast future US CPI rates effectively. By addressing this research problem, the intention is to contribute to the ongoing advancements in the field of inflation forecasting by utilising modern machine learning architectures and to help improve the efficacy of economic decision-making processes.

This research will utilise historical data for each potential determinant. However, it is important to acknowledge certain limitations associated with this approach. Firstly, the reliance on historical data may not fully capture the dynamic nature of such economic factors, and the potential for unforeseen shocks or changes in the future, for example, another pandemic. Secondly, there is potential for gaps or inaccuracies in the data sources, which could impact the model's performance. Regarding the neural network itself, it may be sensitive to changes in economic conditions and susceptible to overfitting, which could reduce its generalisability to newer data. Lastly, the scope of this research is limited to the US economy and its specific CPI determinants, which may not be directly applicable to other economies or regions. Despite these limitations, the study aims to contribute to the field of inflation by employing advanced machine-learning techniques and providing insights into the economic determinants of the US CPI.

Chapter 2 provides the Background, delving into the history of inflation, its importance in the economic landscape, specifics on the Consumer Price Index, and the emerging role of machine learning in enhancing the accuracy of economic forecasting.

Chapter 3 presents a comprehensive literature review, examining existing research on CPI determinants, forecasting methods, and the use of neural networks in economics.

Chapter 4 outlines the Data and Methodology, describing the data sources, the selection of economic determinants, and the process of developing and training the LSTM neural network model.

In Chapter 5, the results are presented, including the findings of the empirical analysis, the identified determinants of CPI, and the performance of the neural network model in forecasting future rates.

Chapter 6 offers a Discussion of the results, interpreting their implications for the field, comparing the performance of the neural network model to traditional forecasting methods, and addressing the research questions.

Finally, Chapter 7 concludes the dissertation, summarizing the research findings, highlighting the contributions to the field, acknowledging limitations, and suggesting avenues for future research.

2 Background

2.1 Historical Context

In the early years of inflation forecasting, the Federal Reserve relied on simple economic models such as the Phillips Curve - which describes an inverse relationship between unemployment and inflation [6] [7]. As the field evolved, they progressed to surveying economic professionals, consumers, and business owners during the mid-20th century [8]. This began in 1968, and the Fed took over this survey in 1990. Around the same time, more complex econometric data were developed by the Fed, incorporating factors such as the money supply, fiscal policies, and unemployment rates. One example is the FRB/US model, a large-scale macroeconomic model developed by the Federal Reserve Board's staff [9].

The transition from traditional econometric models to more advanced techniques began with the adoption of Autoregressive Integrated Moving Average (ARIMA) models in the 1970s, popularised by statisticians George Box and Gwilym Jenkins [10]. The implementation of Bayesian methods, which have been around since the 18th century, in econometric forecasting gained popularity in the early 2000s, which offered a probabilistic approach to inflation forecasting. These were an improvement upon ARIMA models in that they facilitated the integration of prior knowledge and external information, as well as more effectively handling non-linear data [11].

These simple linear models, while providing valuable insights, are often reductionist in their calculations, as they struggle to capture the complex interactions and nonlinear relationships between variables in economic systems.

The Federal Reserve later began using Dynamic Stochastic General Equilibrium (DSGE) models in the mid-2000s [12]. These provide a much more comprehensive framework for understanding the relationships between various economic variables and the inflation rate. These models incorporate microeconomic factors such as the behaviours of households, firms, and policymakers, which allow for a much more in-depth analysis of the economy and the mechanisms driving inflation.

Neural networks have the potential to outperform these traditional forecasting methods due to their ability to capture complex, nonlinear relationships between variables, adapt to evolving economic conditions, and learn from large datasets, ultimately providing more accurate and robust inflation forecasts.

Throughout history, certain periods have highlighted the importance of accurate inflation forecasts. For instance, during the Volcker disinflation period of the early 1980s, aggressive intervention was needed to reduce the level of inflation from a peak of 13.5% in 1980. The Federal Reserve, under the chairmanship of Paul Volcker, implemented contractionary monetary policies to combat the high inflation [13].

Similarly, the recent inflation spike as a result of the COVID-19 pandemic has again highlighted the need for reliable inflation forecasting. The pandemic brought untold disruption to the global economy. Consumers and businesses need accurate forecasts during these times to navigate the challenges and make informed decisions for their financial well-being.

In such periods, forecasting challenges often arise from difficulties in predicting the magnitude of economic shocks or policy interventions, emphasizing the need for continuous improvement in forecasting methods.

2.2 Key Concepts and Terminology

Goods such as food and housing are given a higher weight in the CPI since they are among the largest consumer expenditures. Other less frequently bought goods and services included in the CPI include tobacco products, funeral expenses, and dog collars. The CPI is a Laspeyres index, which means it measures the change in price of a fixed basket of goods and services relative to the weighting of the base year, thus reflecting the change in price of the same goods bought each year.

The inflation rate of an economy will have a multitude of other economic factors that determine or contribute to it. These are the macroeconomic determinants of inflation. Economic theory suggests that changes in inflation can be caused by a multitude of factors, such as the unemployment rate and interest rates. Various economic schools have differing opinions on other causes of inflation. The monetarist school, associated with such economists as Milton Friedman, stressed the role of the money supply - the total amount of money in circulation in an economy at one time - in driving inflation rates [14]. Another school is the Keynesian school, headed by famed British economist John Maynard Keynes. They emphasise the importance of a balance in aggregate demand and aggregate supply in determining inflation [15].

$$AD = C + I + G + (X - M)$$

where C is consumption, I is investment, G is government spending, and (X-M) is the trade surplus/deficit (exports - imports).

Neural networks are a machine learning model whose designs are based on the fundamental design of the human brain. They consist of various layers containing interconnected neurons which process and transmit information, and this structure allows the model to learn complex relationships in the input data. These models have been successfully used for forecasting in many industries, including weather forecasting, traffic predictions, and natural disaster predictions [16, 17]. They are also successfully used for image classification, fraud detection, and medical diagnoses. [18] [19]

The accuracy of a forecasting model is measured using a loss function, which measures the difference between the actual training data and the data predicted by the model. Common loss functions include the Mean Absolute Error (MAE) and the Mean Squared Error (MSE). The Mean Absolute Error is the average absolute difference between the actual data and the predicted data. whereas the Mean Squared Error is the average squared difference between the actual and predicted data. The lower the coefficient returned by the loss function, the closer fit the prediction is to the actual data. Each loss function has different use cases, with MSE punishing larger errors more severely than MAE does.

3 Literature Review

3.1 Systematic and Comprehensive Review

In the literature, various studies have been conducted to understand the determinants of inflation. Greenidge and DaCosta [20] investigated the factors influencing inflation in four Caribbean countries, finding that real national income, money supply, oil prices, world prices, and the unemployment rate were the primary determinants in Barbados, while countries like Trinidad and Tobago were more influenced by changes in oil prices.

Jana Salim examined the determinants of inflation in 10 selected Asian countries between 2006 and 2015, using panel data (a combination of time-series and cross-sectional data) regression model, measuring the respective countries' CPIs [21]. The independent variables included in the scope of the study were the interest rate, GDP, money supply, and public expenditure. The study found that the interest rate and the money supply were significantly and negatively related to inflation, with the money supply being the most influential factor. Okeke et. al. investigated the determinants of inflation in Nigeria [22] and found that the strongest short-term determinants were the Real Output Gap, the Money Supply, Total Government Expenditure, Total Imports, the Unemployment Rate, whereas the long-term determinants were Total Government Expenditure, Total Imports, and the Unemployment Rate.

In another study, a Jordan neural network was employed to forecast the inflation rate of Euro-area countries between 1999 and 2017 [23]. The paper determined the optimal JNN for inflation testing 250 different JNN models.

Other studies test whether the determinants of an economic variable do have long-term relationships. Biswas and Saha conducted cointegration tests on the determinants of India's GDP, analysing whether long-term relationships existed between GDP and the determinants [24]. They employed the Johansen and Juselius multivariate co-integration test and the vector error correction (VEC) model for their analysis. They found that GDP was positively influenced by employment, exports, Foreign Direct Investment (FDI), the money supply, and gross domestic capital formation. They also found negative relationships between India's GDP and inflation and the fiscal deficit.

There are also various papers exploring the use of neural networks for econometric forecasting. Altay's paper demonstrated that "neural networks generated better returns than linear regression models when used as trading strategies", and provided significant evidence of their superiority in predicting the direction of the stock market [25].

Another study by Kokov addressed the question "Can deep neural networks performance surpass that of classical econometric models?" [26]. The research confirmed previous findings "that neural networks outperform ARIMA models for long-term forecasting", with the best-performing neural network architecture of those tested being the LSTM model. However, the performance of both the neural networks and the ARIMA models were hit-and-miss when compared to the persistence model tested. Kokov acknowledges that further work is needed on the models regarding parameter tuning to get a definitive answer on whether neural networks can consistently outperform ARIMA models in single-step and multi-step forecasting, however, the neural networks models, particularly the LSTM, showed great promise.

3.2 Economic Theories

The selection of variables for this study was also informed by considering various economic theories, including monetarist, Keynesian, and supply-side theories on the cause of inflation. Milton Friedman, a prominent monetarist, and Nobel Prize-winning economist, believed that inflation is primarily a result of excessive growth in the money supply. Friedman is quoted as saying "...inflation is always and everywhere a monetary phenomenon in the sense that it is and can be produced only by a more rapid increase in the quantity of money than in output." [14] Friedman emphasised the role of monetary policy, a change in the money supply or interest rates by the central bank, in managing inflation rates.

In contrast, British economist John Maynard Keynes, the founder of Keynesian economics, posed that inflation is caused by demand-pull factors - where increased aggregate demand increases both the price level (inflation) and the level of real output.

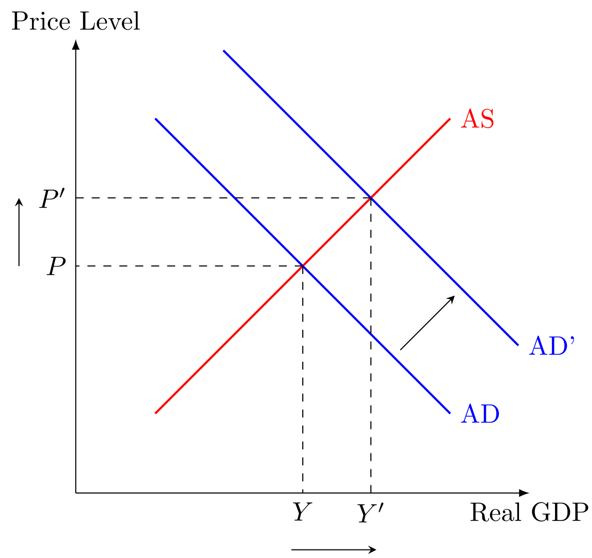


Figure 1: Demand-Pull Inflation on an AD/AS Diagram

Figure 3.1 demonstrates demand-pull inflation on an Aggregate Supply and Demand (AD/AS) diagram.

Demand-pull inflation occurs when the overall demand for goods and services in an economy outpaces the economy's ability to supply them, leading to higher prices. This is represented by a rightward shift in the AD curve, leading to an increase in both Price Level and Real GDP.

The AS curve shows the total amount of goods and services that firms are willing and able to provide at different price levels. The supply curve slopes upwards because as the price level increases, firms have a greater incentive to provide more goods and services since greater profit margins are attainable.

The AD curve shows the total amount of goods and services that consumers are willing and able to purchase at given price levels. The demand curve slopes downwards because as the price of goods and services increases, consumers, firms, and the government have a lower incentive to purchase them, and an increased incentive when the goods and services are at a cheaper price.

Keynes argued that demand-pull inflation was the leading cause of inflation. Economic variables that can cause an increase in AD include increased consumer spending, government spending, and business investment.

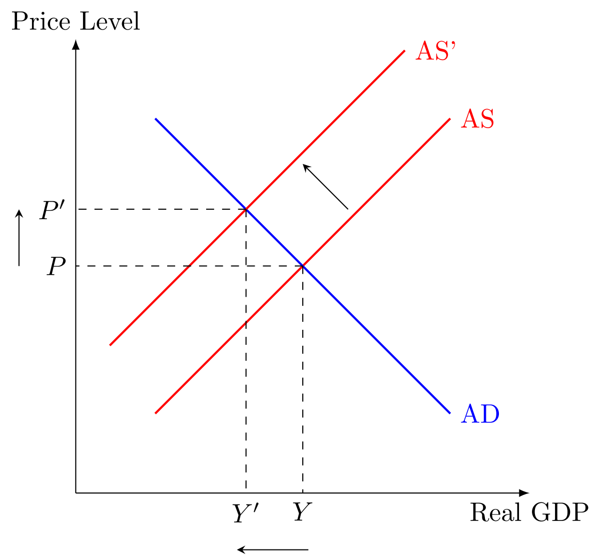


Figure 2: Cost-Push Inflation on an AD/AS Diagram

This diagram shows cost-push inflation. In contrast to demand-pull inflation, cost-push occurs when the price level increases due to supply-side factors such as increased production costs, increased raw material costs, and supply chain disruptions.

Friedrich Hayek, an Austrian economist, and one of the best-known advocates of the Austrian school of economics, focused on the roles of interest rates and credit expansion in causing inflation, similar to the monetarist perspective of Milton Friedman. These key theories and models provided a solid foundation for selecting variables in this study, as they offer insights into the differing opinions on the economic factors that drive inflation.

3.3 Synthesis and Critique

The literature reviewed in this chapter offers valuable insights into the determinants of inflation and the potential use of neural networks for forecasting purposes. However, a critical analysis of these studies reveals several areas where further research and exploration are necessary.

One area of investigation that emerges from the reviewed literature is the question of whether the determinants of inflation in one country, such as Barbados, will match the determinants of inflation in the United States. As different countries have unique economic structures, monetary policies, and fiscal circumstances, it is crucial to recognise that the factors driving inflation might not be universally applicable. Greenidge and DaCosta found in their study that the primary determinants of inflation in Barbados were distinct from those in Trinidad and Tobago [20]. Consequently, further research is required to ascertain the degree to which the determinants of inflation in various countries are similar or divergent.

Expanding on this, further research could explore the application of neural networks to identify the strongest determinants of the US CPI. By incorporating a broad range of variables, researchers can develop more sophisticated models capable of capturing the complex dynamics underlying inflation rates in the United States.

Additionally, Kokov's research highlights the need for further parameter tuning to confirm the best model for single-step and multi-step forecasting. This suggests that future studies could focus on optimising neural network models to enhance their predictive capabilities for inflation forecasting, ensuring that the most accurate and reliable models are employed.

Sestanovic's paper, which employed JNNs to forecast inflation in Euro-area countries, acknowledges that JNNs are "rarely used for macroeconomic time series predictions". In contrast, LSTMs have been proven to provide highly accurate econometric forecasts when compared to other models [26]. Furthermore, considering that the United States is arguably the current economic global powerhouse, it would be worthwhile to investigate the performance of alternative neural network architectures, such as LSTMs, in forecasting US inflation.

3.4 Gaps in the Literature

While the existing literature provides valuable insights into the economic determinants of inflation and the application of neural networks for forecasting various economic variables, several gaps remain unaddressed.

One such research gap is the currently limited exploration of the generalisability of determinants of inflation across different countries and economic contexts. Most of the reviewed studies focus on specific regions or countries, and it is not yet clear whether their findings can be readily applied to other such regions. Further research could address this gap by finding commonalities in the underlying factors influencing inflation rates worldwide.

Furthermore, the existing literature has not yet explored the optimal neural network model for forecasting inflation. There has yet not been such a comparison of various neural network models, including JNNs, CNNs, and RNNs, in producing the optimal forecasts of the Consumer Price Index. Such comparisons could provide valuable insights into the most suitable neural network architectures for this specific purpose.

3.5 Connection to the Research

The research presented in this study aims to address the identified gaps in the literature by examining the strongest economic determinants of the US CPI and using these determinants in a neural network, specifically an LSTM model, to forecast future US CPI rates. Our study fills the research gaps by expanding the scope of the determinants and finding using the LSTM model, which has shown great performance potential, for the US inflation forecasting. This research contributes to a better understanding of the US inflation determinants and provides a framework that can be applied to other economies or regions.

4 Methodology

4.1 Problem Analysis

The first problem that was investigated was to find the economic variables that are most closely linked to the US inflation rate (CPI). The second problem was, using these suitable variables, to then use a neural network model to forecast the future rates of US inflation. 30 years of data, from 1992-2021, will be used to train the models. 5 years of CPI data will be forecast, from 2022 to 2026.

4.2 Development Methodology

An agile methodology was undertaken in this project. Short, focused work sprints were conducted from Monday to Friday. During each sprint, specific tasks and objectives were targeted, with progress tracked daily to ensure continuous improvement and timely completion. At the end of each sprint, a self-review session was held to assess the work completed, evaluate overall progress, and identify any areas for improvement or adjustment. This approach to methodology allowed for flexibility and adaptability in response to evolving requirements, providing a structured framework for addressing any unexpected obstacles.

4.3 Programming Language

The project utilised the Python programming language due to its extensive collection of statistical and deep-learning libraries. Its higher-level syntax makes not only implementing a neural network simpler, but also debugging the network, as the code is much easier to understand than many lower-level languages. This comes at the expense of slower performance, however, performance is not required within this project.

4.3.1 Python Modules

TensorFlow [27], Google's open-source machine learning library was used to create the deep learning model. Keras [28] simplifies and improves the user experience while implementing TensorFlow's functionality. The layers of the networks were initialised and altered using this module.

The scikit-learn [29] module's 'preprocessing' and 'models' libraries were utilised to normalise the data, and to create the test loss metrics, used to measure the performance of each model.

Pandas [30] was used to load the time-series data from their respective CSV files, to preprocess this data by handling missing data values for example, and to merge the datasets. Converting datasets to DataFrames allows for simple and efficient data handling and manipulation.

Numpy [31] was used to handle arrays and their operations, including splitting into training and testing data, calculating averages, and finding minimums and maximums.

Matplotlib [32] was used to plot the data from the CSV files and to map on top of that the forecast produced by the network. This helps to provide a visualisation of the network's output in a user-friendly manner.

4.4 Coding Environment

Jupyter Notebook was the chosen development environment that was used for several reasons, including its ability to run small segments of code individually and its pre-installation of the aforementioned Python modules. It also supports inline visualisation, allowing plots to be displayed and results to be shown directly within the notebook, making it easier to interpret and share the results.

4.5 Data Collection

The data was collected from numerous sources, primarily online data repositories including The World Bank Open Data repository [33] and The Federal Reserve Bank of St. Louis [34]. Other sources used include Yahoo Finance [35] and The Federal Reserve Bank of San Francisco [36]. Both of these sources provide a wealth of economic data with regular updates, ensuring the accuracy and reliability of the data. The data was collected in .csv file format, which facilitated easy integration into the analysis using the Pandas Python library for data manipulation.

The choice of economic variables to include in this analysis was derived from two primary sources. The first was from the literature review I conducted on other papers that researched the determinants of inflation. The second was variables that economic theory suggests have effects on inflation. Through both of these methods, I collated a total of 19 economic variables to include in the analysis. Those variables are as follows:

Budget Deficit [37], Capacity Utilisation [38], CPI [39], DXY Dollar Index [40], Electricity Prices [41], Export Price [42], Gas Prices [43], GDP [44], GNI [45], House Prices [46], Import Price [47], Lending Rate [48], Money Supply [49], PPI [50], Real Interest Rate [51], Retail Sales [52], Total Factor Productivity [53], Unemployment Rate [54] Wage Growth [55]

These variables encompassed a wide range of economic indicators, including the US Money Supply (M2), with money supply being the most often cited determinant of inflation from the literature. Additional variables, such as the US GDP [44], the Producer Price Index (PPI) [50], and interest rates [51] were included given their frequent appearances in the literature review.

Moreover, other variables considered were the Capacity Utilisation of the US economy [38], the US Unemployment Rate [54], and US Wage Growth [55], which were also included. These variables were selected based on their potential influence on inflation as suggested by economic theory. The US CPI time series was also downloaded for all of the other variables to be analysed against [39].

To ensure the robustness of the analysis, the data was collected with an annual frequency, spanning several decades. Some datasets contained over 100 years of data, with others only starting in 1992. A monthly granularity would have perhaps improved the model and helped provide more accurate forecasts; however, not all of the data was available in a monthly format. Despite this limitation, the annual data still provided a large sample size for the analysis and was enough to capture the dynamic relationships between the selected economic variables and inflation over time.

4.6 Correlation Test

My first step in finding the strongest determinants was to conduct a correlation analysis between the time series. The Pearson correlation coefficient test is quite a straightforward test.

4.6.1 Data Manipulation

Since the Pearson correlation test uses pairwise comparisons, each of the datasets had to be the same length. The shortest dataset began in 1992, so all data before 1992 was deleted from every time series.

4.6.2 Correlation Test Results

The Pearson correlation test produced the following data:

1. Lending Rate: 0.73134 2. Electricity Prices: -0.63339 3. GNI: -0.61459 4. House Prices: -0.59350 5. GDP: -0.41236 6. Capacity Utilisation: 0.37187 7. Total Factor Productivity: -0.36881 8. Wage Growth: -0.36332 9. PPI: -0.32122 10. Export Price: -0.31319 11. Import Price: -0.29134 12. Budget Deficit: -0.23902 13. Unemployment Rate: 0.12558 14. Retail Sales: -0.11408 15. Money Supply: 0.10776 16. Gas Prices: -0.09896 17. Real Interest Rate: 0.05933 18. DXY Dollar Index: 0.04564

4.7 Cointegration Test

To further check whether these time series had a long-term relationship with the CPI, a cointegration test was conducted.

The Johansen cointegration test was run on the datasets: This test is used to determine whether two or more time-series variables have a long-term equilibrium relationship, i.e., they are cointegrated. [56]

A long-term equilibrium relationship between time-series variables means that even though the individual variables may be non-stationary and exhibit random walk-like behavior, there exists a stationary linear combination of these variables. This stationary linear combination implies that the variables tend to move together in the long run, maintaining a stable relationship. In other words, deviations from the equilibrium are temporary, and the variables will converge back to the equilibrium over time.

The Johansen cointegration test works under a few assumptions of the data. One such assumption is that the variables under consideration are integrated of order 1 (i.e., I(1)), which means they become stationary after taking the first difference.

4.7.1 Stationarity Tests

A stationary time series is one whose characteristics or properties remain constant and unaffected by the time at which the series is observed. A stationary time series has no trend or seasonality and has a constant mean, variance, and autocorrelation.

The Dickey-Fuller test checks if a time series is stationary [57]. It is a hypothesis test where the null hypothesis is that a unit root is present, and the alternative hypothesis is stationarity. The presence of a unit root suggests that exhibits a stochastic trend with a varying mean and/or variance over time.

The Dickey-Fuller test checks whether ϕ is 0 in the following model:

$$y_t = \alpha + \beta t + \phi y_{t-1} + \varepsilon_t$$

Which can be rewritten as:

$$\Delta y_t = y_t - y_{t-1} = \alpha + \beta t + \gamma y_{t-1} + \varepsilon_t$$

where y_t is the data set, α is the intercept term, ϕ is the autocorrelation coefficient, and ε_t is the error or residual term. Rewriting the equation in this form allows a linear regression model of δy_t to be run against t and y_{t-1}.

The Augmented Dickey-Fuller test (ADF) is an extension of the Dickey-Fuller test that adds more differencing terms to the model, allowing for higher-order autoregressive processes.

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t$$

Any variables that affect inflation will have a lag, especially if it's a change in economic policy. Recognition lag, action lag, and impact lag are all present in that case, so this model must be used to account for these lags.

p is the optimal number of lags for the model. The inclusion of α and β means that the model will detect the presence of a drift term and a time trend respectively.

The AIC autolag that comes included in the *statsmodels.tsa.stattools.adfuller* module was used. Using this feature, the number of lags is chosen to minimize the corresponding information criterion [58].

4.7.2 Stationarity Test Results

Table 1: Results of the Augmented Dickey-Fuller Test on Each Time Series

Dataset	**Unmodified ADF**	**Diff Once**	**Diff Twice**	**Diff Thrice**
Budget Deficit	**1.00000**	0.00021	-	-
Capacity Utilisation	0.00065	-	-	-
CPI	**0.21862**	0.00000	-	-
DXY Dollar Index	**0.38719**	0.00002	-	-
Electricity Prices	**0.97803**	0.03289	-	-
Export Price	**0.99894**	0.00758	-	-
Gas Prices	**0.83699**	0.00060	-	-
GDP	0.99683	0.97216	**0.31687**	0.00000
GNI	1.00000	0.94260	**0.39248**	0.00000
House Prices	0.99768	**0.92533**	0.02171	-
Import Price	**0.83268**	0.00001	-	-
Lending Rate	**0.32504**	0.00000	-	-
Money Supply	**0.91116**	0.00000	-	-
PPI	1.00000	**0.81314**	0.00101	-
Real Interest Rate	**0.46021**	0.01067	-	-
Retail Sales	**0.99892**	0.02423	-	-
Total Factor Productivity	0.00000	-	-	-
Unemployment Rate	0.04831	-	-	-
Wage Growth	**0.89782**	0.00000	-	-

This table shows the results of the ADF tests on the datasets and their differences. The table goes up until the third difference, at which point every time series had achieved stationarity. Since the Johansen test wants the datasets in integration order, I(1), form, the time series that would become stationary with one more round of differencing was used. These datasets are highlighted in bold in the table.

4.7.3 Data Manipulation

Just like with the Pearson test, the datasets in the Johansen cointegration test must be of the same length. Almost all datasets had to be differenced at least once before they became stationary, according to the Augmented Dickey-Fuller test, meaning they were of integration order I(1). Some of the data had to be differenced 3 times before becoming stationary, making them I(3). Since differencing the data makes the time series one element shorter each time, the CPI time series had to be truncated to ensure they were the same length.

These new datasets were again checked over with the ADF test to ensure that they were still stationary. The stationarity was not greatly affected since only the first 2 years were truncated in the worst-case scenario.

This does mean that some datasets were compared to the CPI dataset with 1, 2, or 3 extra years, however, the effect this would have on the outcome of the test was assumed to be minimal enough that this method was still pursued.

4.7.4 Cointegration Test Results

The critical values for the test were calculated to be:

Table 2: Critical Values

	1%	5%	10%
Trace Statistic	13.4294	15.4943	19.9349
Max-Eigen	2.7055	3.8415	6.6349

If the Trace and Max-Eigen statistics are higher than the critical values, this is evidence of a long-term equilibrium relationship between this dataset and the CPI. For this test, the 5% significance level critical levels were deemed sufficient to demonstrate such a relationship.

The results of the Johansen cointegration test were as follows:

Table 3: Johansen Cointegration Test Results

Variable	**Eigenvalue 1**	**Eigenvalue 2**	**Trace Statistic**	**Max-Eigen Statistic**
Budget Deficit	0.18633459	0.06179119	32.39865443	24.74472522
Capacity Utilisation	0.5108493	0.18669908	55.30432473	42.90507892
DXY Dollar Index	0.20850226	0.02767734	15.97564605	14.26352391
Electricity Prices	0.34016936	0.01030567	25.99400442	25.36209708
Export Price	0.21623591	0.00121892	14.93687897	14.86247947
Gas Prices	1.99985838e-01	8.58244965e-05	1.36159123e+01	1.36106768e+01
GDP	0.57639122	0.14432059	60.88826624	51.5366963
GNI	0.55104086	0.14759542	57.63104335	48.04940319
House Prices	0.13869841	0.03680704	11.20872416	8.95863357
Import Price	0.21457517	0.00318601	14.92801837	14.73336174
Lending Rate	0.20400673	0.12777945	21.89265084	13.68987278
Money Supply	0.12836036	0.00764638	8.99340745	8.51751014
PPI	0.35275607	0.04292697	51.24311458	46.54842782
Real Interest Rate	0.23710959	0.10834896	23.11927931	16.23845338
Retail Sales	0.20438856	0.05704774	17.53042267	13.94730564
Total Factor Productivity	0.53268577	0.32761444	84.51040056	55.53499594
Wage Growth	0.32469789	0.04361941	26.66886172	23.94830223

For a long-term equilibrium relationship to exist between two time series, the Trace and Max-Eigen statistics should be higher than the critical values, in this case at the 5% significance level.

Using that criterion, this table shows that the following variables exhibited strong relationships with the CPI in the cointegration test; i.e., both the Trace Statistic and the Max-Eigen statistic exceeded the critical values at the 5% significance level:

Budget Deficit, Capacity Utilisation, DXY Dollar Index, Electricity Prices, GDP, GNI, Lending Rate, PPI, Real Interest Rate, Retail Sales, Total Factor Productivity, Wage Growth.

4.8 Strongest Correlating Determinants

Taking into account both the Pearson and Johansen tests, the following variables were shown to have the strongest relationships with the CPI data (in no particular order):

Capacity Utilisation, Electricity Prices, GDP, GNI, House Prices, Lending Rate, PPI, Total Factor Productivity, Wage Growth

4.8.1 Strengths and Limitations of Selected Variables

The selected variables offer a comprehensive representation of various economic factors that can impact inflation. Their strengths lie in their strong correlation or cointegration with CPI data, indicating a robust relationship. Moreover, their economic rationale supports their inclusion in the forecasting model. Some of the variables, such as Lending Rate, GDP, and Wage Growth, impact consumer spending and demand for goods and services, thereby directly affecting inflation. Others, like Electricity Prices and PPI, reflect changes in production costs that indirectly influence inflation through their effect on consumer prices. For example, higher lending rates can lead to reduced spending and lower inflationary pressure, while rising electricity prices can increase production costs and contribute to inflation. By considering these variables and their economic interpretations, the model captures a comprehensive view of the factors that drive inflation in the economy.

However, there are some limitations to consider. First, these variables might not capture all relevant factors influencing CPI, as there may be other unobserved variables or external shocks affecting inflation. Second, the variables' relationships with CPI might change over time, potentially reducing the accuracy of the forecasting model. Lastly, multicollinearity among the variables could lead to issues in estimating the model parameters, as some variables might be highly correlated with each other.

5 Forecasting

Now that the strongest determining variables have been identified, the inflation rate can be forecast.

5.1 Neural Networks

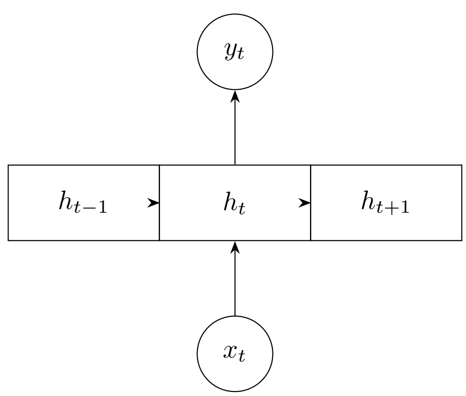
Artificial intelligence is the use of software and hardware to perform tasks that would typically require human intelligence. Such tasks include speech recognition and captioning, and image classification. AI systems are capable of thinking and acting rationally and humanly [59], and are designed to simulate the human cognitive processes.

Neural networks are one implementation of artificial intelligence. They consist of interconnected layers, with each layer containing multiple nodes, or neurons. Each layer processes the input data and passes the result to the next layer. These networks are inspired by the structure and functionality of the human brain, designed to mimic its intricate connections to process and analyse vast amounts of information.

5.2 RNNs

A recurrent neural network (RNN) is a class of neural network that is specifically designed to handle sequential data such as natural language text and time-series data. RNNs differ from typical neural networks in that they have recurrent connections between their nodes within their hidden layers [60]. A typical network's nodes will only travel in one direction, from input to output. These recurrent connections create loops in the network, and this allows the network to retain some memory, or context for the data, across its time steps. It is this memory that makes RNNs especially well suited for use with such time-series data where dependencies between the data points exist.

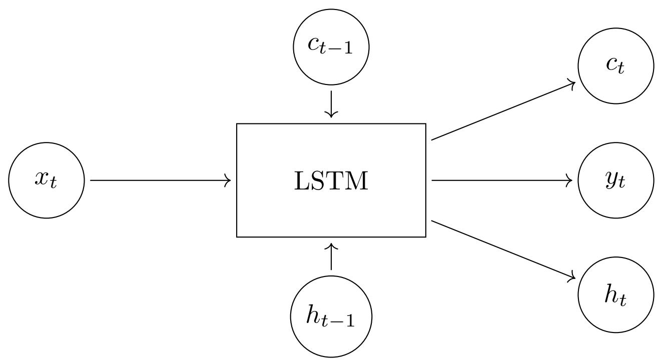
This diagram shows a diagram of an example RNN.



The RNN architecture consists of an input neuron (x_t), a hidden state neuron (h_t), and an output neuron (y_t). The input neuron (x_t) feeds data into the hidden state neuron (h_t), which in turn produces the output (y_t) for the current time step.

5.3 LSTM

A Long-Short Term Model (LSTM) is a particular type of RNN:



An LSTM is a more complex version of a typical RNN that mitigates issues that are present in typical RNNs. LSTMs can remember long-term dependencies between datasets. The diagram shows how information flows through an LSTM. The input value x_t, cell state c_{t-1}, and hidden state h_{t-1} are fed into the LSTM cell. The LSTM cell processes this information and generates the output y_t, the updated cell state c_t, and the updated hidden state h_t [61].

An LSTM differs from a typical RNN in that it implements gating mechanisms to circumvent common problems that an RNN would run into, such as the exploding gradient and the vanishing gradient problem. The four gates within an LSTM are the input gate, forget gate, the cell update gate, and the output gate [62]. These gates manage the flow of information within the network, allowing it to selectively remember, update and output information, helping to capture the long-term dependencies within the data.

LSTM's real-world financial applications include stock price predictions [63], algorithmic trading [64], and portfolio optimisation [65].

When processing a dataset, the LSTM network initialises the cell states and hidden states. For each time step in the dataset, the input value x_t, cell state c_{t-1}, and hidden state h_{t-1} are fed into the network. The network processes this information, implementing its gating mechanism - using its input, output and forget gates, and generates the output y_t, the updated cell state c_t, and the updated hidden state h_t. In a larger LSTM network, LSTM cells are connected with the output of one being the input for the next. This architecture allows the network to remember long-term dependencies between datasets.

5.3.1 Neurons

Neurons are the fundamental computational unit within a neural network, responsible for processing the input data and transmitting it between the layers of the network. A higher number of neurons can allow the network to discover more complex relationships within the data, but this increases the risk of overfitting and increases computational resources. Various permutations of the number of neurons on each of the 3 LSTM layers were tested, each having either 50, 100, or 150 neurons.

5.3.2 Dropout Layers

Dropout layers are a regularisation technique used to prevent the model from overfitting the data - this is where the model finds short-term trends or random fluctuations, "noise", in the data and extrapolates them believing that these trends continue in the long term. Dropout layers help to mitigate this overfitting by 'dropping' or deactivating neurons selected at random during the training. During each training iteration, each neuron in the network has an x probability of being dropped, x being the Dropout coefficient. Using Dropout layers means the network is less reliant on each neuron, making it more robust and less prone to overfitting.

Selecting an optimal dropout rate is very important, but the optimal rate depends on the complexity of the model and the dataset. Experimenting with different dropout coefficients was very important to do. Too high a dropout rate can lead to underfitting if the dropout coefficient is too large for a small network, and can slow down the training process. Too low of a dropout rate can lead to overfitting.

Output dropout was used in this project, where the dropout layers were applied to the output of the LSTM model. This has a more direct effect on the output of the model than input and recurrent dropout, as it targets the outputs of the final layer. Dropout coefficients of 0, 0.2, and 0.5 were tested. These mean that in each training iteration, 0%, 20%, and 50% of the neurons were dropped during training, along with their connections.

Dropout is only applied during the training phase, and all neurons are active during the forecasting, ensuring the full capacity of the network is utilised.

5.3.3 Dense Layer

The function of a dense layer, or a fully connected layer, is to consider all the features learned from the input data and to produce an output. In a dense layer, each neuron is connected to every neuron in the previous layer.

A Dense layer with a single output neuron was added to the model after the last LSTM and Dropout layers to generate the final output. This allowed the network to aggregate the information from the previous layers to produce a single continuous value as the prediction.

5.3.4 tanh Activation Function

Activation functions are what introduce non-linearity into the network. This means that the outputs of the neurons are transformed so that it's not simply a linear combination of its inputs. This non-linearity allows the model to find complex relationships in the data. The two activation functions within the scope of this project were the hyperbolic tangent (tanh) function and the Rectified Linear Unit (ReLU) function.

The tanh function maps its input values onto the tanh curve - an S-shaped curve bound between -1 and 1. It uses the following formula:

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

where x is the input value. Values that are close to 0 remain relatively unchanged, whereas values further from 0 are given a value closer to the extremities of -1 and 1. Since the scope of the tanh function includes both positive and negative numbers, positive and negative trends in the data can be captured.

The tanh activation function can experience the vanishing gradient problem. During backpropagation, the gradients of the loss function are multiplied by the derivatives of the output of the activation function.

$$\frac{d\tanh(x)}{dx} = 1 - \tanh^2(x)$$

Due to the nature of the tanh cure, the derivatives of values that are far from 0 become very close to 0. Because of this, the gradients can become very small as the inputs are repeatedly propagated through the network. However, this is not an issue since LSTMs implement gating mechanisms that prevent the vanishing gradient problem from occurring.

5.3.5 ReLU Activation Function

The ReLU function is a simpler activation function with the following formula:

$$\mathrm{ReLU}(x) = \max(0, x)$$

If the input value x is greater than or equal to 0, then it is mapped to x. If the input value is less than 0, it is mapped to 0.

$$\frac{d\mathrm{ReLU}(x)}{dx} = \begin{cases} 1, & \text{if } x > 0 \\ 0, & \text{if } x < 0 \end{cases}$$

The ReLU function alleviates the vanishing gradient problem by having a constant derivative of 1 for all positive input values.

5.3.6 Optimiser Function

An optimiser function is a method of adjusting the weights of the neural network during training, with the goal of minimising loss; the error between the predicted values and the actual values. These weights will then be used to, in theory, provide the most accurate forecast.
The Adaptive Movement Estimator (Adam) is a widely used optimiser. It computes two moving averages for each weight. The first moment (the mean) is a momentum constant calculated using the gradient's direction and magnitude, and it aims to accelerate convergence. This is the average of the past gradients, and since it's converging, this average is exponentially decaying.

The second moment (the variance) is an average of the squared gradients. This measures the size of the changes between the recent gradients, and this allows the optimiser to adapt the learning rate for each weight accordingly.

5.3.7 Epochs

Epochs are batches of training iterations. This is the number of times the network iterates through the entire dataset during training. Just like the number of dropouts, the number of Epochs is important to combat the over- and underfitting of the models. 100 Epochs were used for training in each model with a batch size of 1. This is quite a large number of Epochs which allowed for better performance (therefore more accurate weights) and a faster convergence, at the expense of a slower training time.

5.3.8 Window Size

A window size of 4 was used. This means the model takes into account the previous 4 years of data, allowing it to capture the short-term trends and dependencies between the variables.

5.3.9 Loss Function

The mean squared error was used for the loss function. It calculates the average squared difference between the predicted value and the actual value. It uses the following formula:

$$\text{Mean Squared Loss} = \frac{1}{N \cdot T} \sum_{i=1}^{N} \sum_{t=1}^{T} (y_{i,t} - \hat{y}_{i,t})^2$$

Where:

- N is the number of samples in the dataset

- T is the length of the sequence (number of time steps)
- $y_{i,t}$ is the true target value for the ith sample at time step t
- $\hat{y}_{i,t}$ is the predicted output for the ith sample at time step t

This loss function was chosen for its simple implementation and its tougher punishment on worse predictions than the Mean Average Error (MAE).

5.3.10 LSTM Layer Structure

The LSTM architecture utilised in this project consists of two / three LSTM layers, each followed by a Dropout layer, and a final Dense layer. The first one / two LSTM layers are designed with a 'return_sequences' parameter set to True, enabling them to pass sequences to the subsequent LSTM layers. After each LSTM layer, a Dropout layer is incorporated to prevent overfitting by dropping a certain percentage of neurons during training. Lastly, a Dense layer with a single output node is added to generate the final prediction.

5.4 Normalising the Data

MinMaxScaler is a preprocessing technique that transforms the data so that it lies within the range of 0 and 1.

$$\text{Scaled Value} = \frac{value - min}{max - min}$$

The minimum and maximum values for each feature are found and the remaining data is scaled accordingly. Normalising each feature in this fashion ensures that no one feature has an undue or disproportionate influence on the network.

5.5 Forecast Network

Using the itertools module, different variations of the neural networks were created, using different sizes of the hidden layers, the different activation functions, and varying numbers of dropout layers.

Each iteration of the network performed its prediction, and each prediction was compared against the actual CPI data. The Mean Squared Error between these 2 was calculated and the network that had the lowest mean squared error, in other words, the best prediction, was used for the future forecasting.

5.5.1 Training and Testing Split

A total of 216 network configurations were tested. 54 of those models consisted of 2 LSTM layers, while the other 162 used 3 LSTM layers. All 2 and 3-layer permutations of 50, 100, and 150 layers were tested, with dropout rates of 0.0, 0.2, 0.5, and either the tanh or ReLU activation function.

The first 55% of the dataset was used for training the network. The next 25% was used to test each network. The final 20% of the data was used for the forecasting. This data split provides an optimal balance for training, testing, and forecasting, ensuring that the neural network can effectively learn underlying patterns in the data, while also allowing for robust evaluation of its performance and minimizing the risk of overfitting.

6 Results

6.1 Strongest Determinants Found

As discussed in the methodology section, the strongest determinants of CPI found were: Lending Rate, Electricity Prices, GNI, House Prices, GDP, Capacity Utilisation, Total Factor Productivity, Wage Growth, and PPI.

This analysis of the determinants has implications for understanding the complex relationships between various economic factors and the US CPI. By identifying the strongest determinants, we can gain a better understanding of the key drivers of inflation and thus devise more targeted and effective monetary policies.

6.2 US CPI Forecasts

The following figure shows how the highest-performing network forecasted the CPI data compared to the actual data during its training and testing:

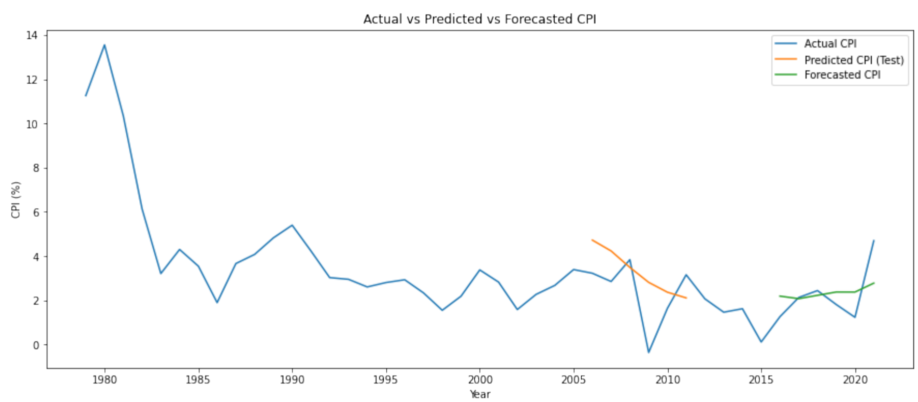


Figure 3: Actual vs Predicted vs Forecasted CPI

The blue line represents the actual CPI values from the dataset. The orange line represents the predicted CPI values for the test data - this is what determined the mean-squared error for each model. The green line represents the forecasted CPI values for the forecast data using the best model. The model accurately predicted a decline in the CPI in the testing phase but failed to fully capture the extent of the decline and the sharp reversal. The end forecast also captured the uptrend but again failed to capture its severity.

The following figure shows the forecast of the future CPI data this model produced:

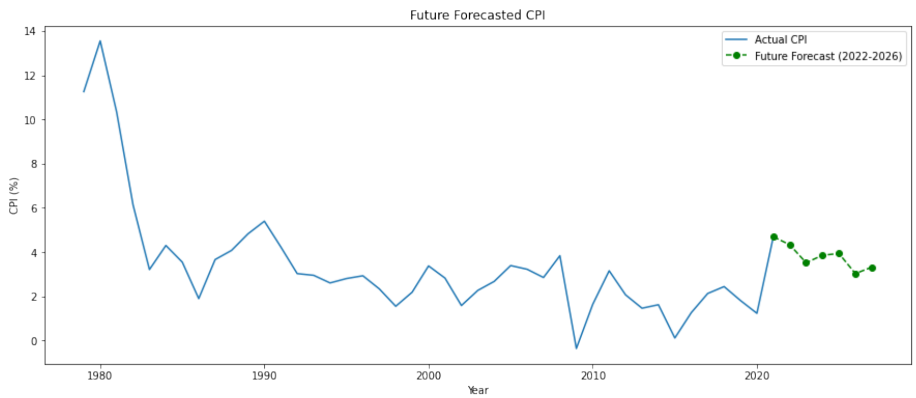


Figure 4: Future Forecast of CPI from 2022 to 2026

This plot shows what the best-performing model forecasts for the US CPI from 2022 to 2026. The model forecasts the following data points: 3.52% in 2022, 3.86% in 2023, 3.94% in 2024, 3.03% in 2025, and 3.32% in 2026. This is a moderate downward trend in the CPI over the coming years, but it will remain above the Federal Reserve's target of 2%.

The forecasted higher-than-target US CPI rates from 2022 to 2026 have significant implications for monetary and fiscal policies, businesses, and investors. Policymakers may need to adjust interest rates and fiscal measures to address inflationary pressures, while businesses and investors must adapt their strategies to cope with increased costs and changing asset values. Consumers may also face reduced purchasing power, impacting spending habits and overall economic growth. However, while this inflation forecast is higher than the 2% target, it is still down from the peak of 2021, so the downward trend may alleviate some concerns and provide a more stable economic environment for businesses, investors, and consumers in the coming years.

6.3 Network Performance Analysis

This best-performing model used three LSTM layers, the first of size 100, the second of 50, and the third of 150 neurons. It used the ReLU activation function and a dropout_rate of 0.5.

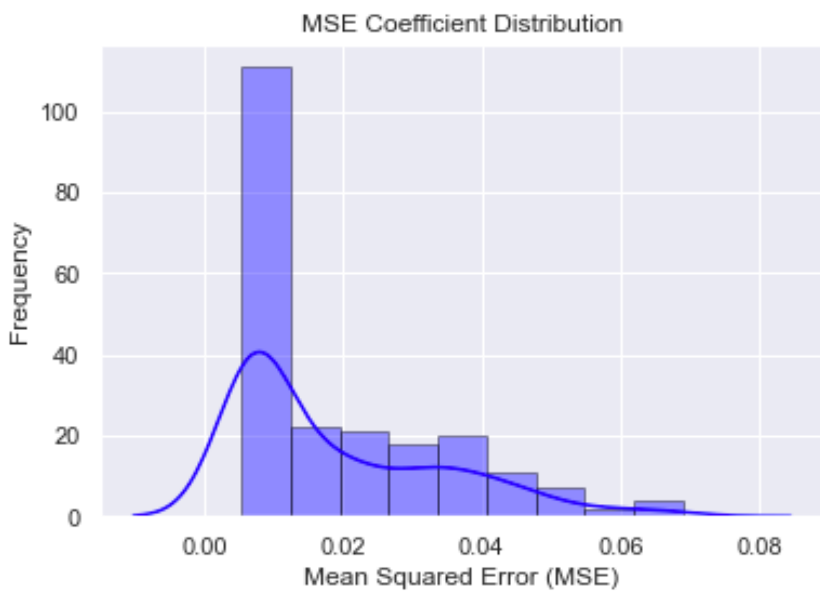
The lowest Mean Squared Error recorded was 0.005308, with the average Mean Squared Error being 0.0190105. The Root Mean Squared Error (RMSE) of this best model is 0.072856. This means that the average prediction of the model during training was only 0.072856 units away from the actual value. This score is 89.2% better than the average RMSE of 0.137879.

The median test loss was 0.011821, and the standard deviation, δ, was 0.015240.

The top 50 performing neural network models, had test loss scores ranging from 0.005308 to 0.006706. Of these top 50 best-performing models, 45 of them used the ReLU activation function, with the remaining 5 using tanh. This indicates that ReLU, despite being a simple model, is well-suited for capturing the relationships between the input economic determinants and the output CPI rates.

Dropout rates of 0.2 and 0.5 performed slightly better than the 0.0 dropout rate, with only 7 of the top 50 models using a 0.0 dropout rate. This suggests that using a higher dropout rate as a regularisation technique helped to prevent overfitting and improved the model's generalisation capability.

Layer configurations seem to vary quite a bit among the top models, however, all of the top 50 models used 3 layers. More investigation may be needed to determine the optimal architecture.



Here is a histogram and kernel density estimation (KDE) plot for the distribution of Mean Squared Error (MSE) values across the set of models.

The distribution is positively skewed, with The vast majority of the test losses recorded lay between 0.005 and 0.013. As the MSE values increase, the frequency of their occurrence rapidly decreases.

7 Discussion

This study aimed to identify the strongest economic determinants of the US CPI and to use these determinants in a neural network to forecast future US CPI rates. The study found that the most influential factors affecting the US CPI were Electricity Prices, Wage Growth, PPI, GDP, GNI, Capacity Utilization, and Total Factor Productivity.

These findings differ with the existing literature that emphasises the role of various economic determinants in understanding and forecasting inflation. Previous studies have identified determinants such as Money Supply, Interest Rates, and Real National Income as significant contributors to inflation. This paper focussed on the US economy, so it is little surprise that the determinants of inflation would differ between two entirely different economies. Our research supports and expands on this understanding by incorporating additional factors like Electricity Prices, GNI, Capacity Utilization, and Total Factor Productivity.

Each of these determinants plays a critical role in understanding the dynamics of inflation. For instance, wage growth can lead to increased consumer demand, resulting in higher inflation as companies raise prices to match increased production costs. Capacity Utilisation reflects the level of economic activity, with higher utilisation rates indicating increased demand for goods and services, thereby exerting upward pressure on prices. Similarly, Total Factor Productivity can influence inflation through its impact on the overall efficiency and productivity of an economy.

The best LSTM model configuration found for predicting future CPI rates was 3 layers of size [100, 50, 150] with the ReLU activation function and a dropout rate of 0.5. The model achieved a test loss of 0.005308, demonstrating its effectiveness in capturing the patterns and relationships among the determinants.

According to the developed model the US CPI will follow a moderate downward trend, decreasing from the recent spike during the COVID pandemic.

This study contributes to the existing body of knowledge by employing an LSTM neural network model to forecast future US CPI rates based on these determinants.

As mentioned in the Results section, the predicted inflation rates have significant implications for the overall economy, monetary policy, and financial markets. For example, a higher inflation rate may prompt central banks to tighten monetary policy, affecting interest rates and investment decisions.

Understanding these forecasts can help policymakers and market participants make informed decisions in response to evolving inflationary pressures. Accurate inflation forecasts are crucial for central banks and policymakers as they formulate and implement monetary policies. By comprehending the future trajectory of inflation, they can make better decisions regarding interest rates and other tools to maintain price stability and support economic growth.

Moreover, businesses can benefit from these forecasts in making informed decisions about pricing, production levels, and inventory management. By anticipating the future direction of inflation, companies can better understand changes in consumer demand, input costs, and the overall business environment, allowing them to adapt their strategies accordingly.

Consumers can use insights from this study to make informed decisions about their personal finances, adjusting their financial plans based on the expected inflation rate. Additionally, economic researchers and analysts can adopt the LSTM neural network model for forecasting inflation rates in other economies or regions, contributing to better global policy decisions.

The study successfully identified key economic determinants of the US CPI, including Electricity Prices, Wage Growth, PPI, GDP, GNI, Capacity Utilisation, and Total Factor Productivity. This expands on existing literature by incorporating a more comprehensive set of factors that influence inflation.

An LSTM neural network model was successfully employed to forecast future US CPI rates based on the identified determinants. The LSTM model provided forecasts of future inflation rates for the period from 2021 to 2026, offering valuable insights into the expected trajectory of US inflation.

The research has contributed to the field of inflation forecasting by demonstrating the potential of LSTM neural networks for accurate inflation prediction, expanding on the set of influential determinants, and providing a framework that can be applied to other economies or regions.

Avenues for further research include finding the optimal LSTM structure for such forecasting. This study found the best model of the permutations tested, but there may be other configurations that yield even better performance. Researchers could employ techniques like Bayesian optimisation or genetic algorithms to search for the optimal LSTM architecture more efficiently.

Another direction for future research is to explore additional determinants that might improve the forecasting accuracy of the model. The scope of the determinants included in further studies could be expanded further still. Incorporating variables such as consumer sentiment, labor market indicators, or international trade data could reveal more intricate relationships and provide a more comprehensive understanding of inflation dynamics.

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