Using Neural Networks to Predict U.S. Corporate Profits on Electronic Goods

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11/03/2023

Inspirit AI Research Project

Abstract

The 2018 trade war between the United States and China, COVID-19, supply chain disruptions, component costs, and post-COVID consumer behavior have all created negative impacts on U.S. corporate profits on electronic goods. The goal of this project is to train two neural network AI models: a Multi-Layer Perceptron (MLP) neural network and a Long Short-Term Memory (LSTM) neural network, to predict U.S. corporate profits on electronic goods into the future. We introduce 1) the datasets used for our models, 2) describe our MLP neural network AI model and its corresponding results, 3) describe our LSTM neural network AI model and its corresponding results, and finally 4) summarize our findings and offer suggestions for future research into this area of study. Our hypothesis for the project was that even though there was a boost to U.S. corporate profits after COVID-19 due to re-opening of the economy and through government aid, these gains were completely offset by the much stronger factor of supply chain inefficiencies, thus bringing these profits down. Our results show that supply chain inefficiencies have begun to abate worldwide and as they do, growth in corporate profits continues to stabilize to pre-pandemic levels.

1. Introduction

For this AI research project we chose to closely study how U.S. corporate profits have been changing over time for electronic goods. We wanted to first learn what factors have been most important in affecting these profits and then to use real-world datasets and AI modeling to predict where these corporate profits are heading into the future.

One factor that is heavily influencing U.S. corporate profits on electronic goods is a significant reduction of Chinese exports to the U.S. since the trade war between the countries started in July 2018. For 15 months beginning in July 2018, the Trump administration applied tariffs to more and more imports from China. Thus far, the Biden administration has chosen to keep these duties in place. Goods in which a 25% tariff has been imposed includes IT hardware and consumer electronics, such as network servers, modems, routers, as well as wireless headphones and smartwatches. U.S. imports from China of these products are down 62% since the 25% tariffs were imposed, whereas U.S. imports from the rest of the world are now 60% higher. China's share of U.S. imports of IT hardware and consumer electronics has been cut by nearly two-thirds, from 38% to 13% [1]. These changes in the worldwide distribution of U.S. imports of electronic goods are illustrated in Figure 1 below.

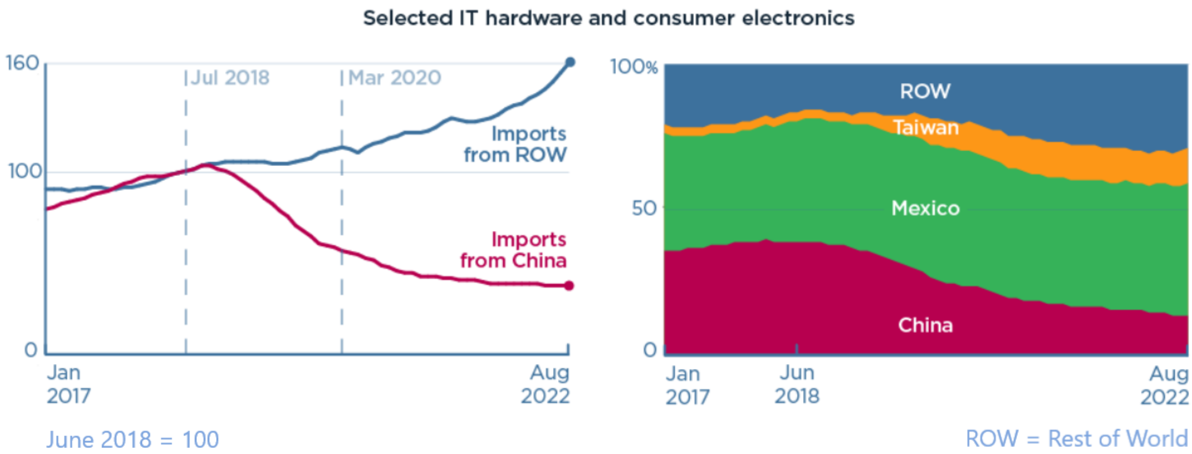

Figure 1.

Another factor is post-COVID changes in U.S. consumer behavior. After a short-lived rebound in the spring of 2023, goods exports from China resumed a long-term slide that dates to October 2022, when consumers in Western developed countries began shifting their spending away from buying furniture and electronic gadgets, and instead diverted it toward other expenses. Worsening geopolitical tensions between Beijing and the U.S. have also prompted some U.S. manufacturers to reduce their reliance on China's supply chain, which in turn is expected to continue to erode trade ties between the two countries. Compared with 2022, China's exports to the U.S. and European Union have plunged by more than 20% [2].

Another large factor in changes in U.S. corporate profits on electronic goods is that of COVID-19 which started in March of 2020 and ended in February of 2021. Both the beginning date and end date of COVID-19 had extreme impacts on imports and exports of every country in the world.

Another significant factor has been major disruptions to the global supply chain or supply chain pressure. Significant supply chain pressure began in January 2020, continued to worsen until January 2021, and has since improved on a monthly basis to present day [3].

Our goal was to use real-world datasets that reflect these factors on U.S. corporate profits on electronic goods, to train two separate AI models (MLP and LSTM), and to use these models to accurately predict future profits.

2. Materials and Methods

2.1. Datasets

For this project we used openly available datasets taken from online sources to train our MLP and LSTM neural network AI models.

The first dataset (DS1) comes from the St. Louis Federal Reserve Economic Data (FRED) website, and measures corporate profits of the U.S. for computer/electronic products from 2001 through 2023 [4]. Figure 2 below illustrates this dataset. This is the dataset that we are trying to train our AI models to mimic.

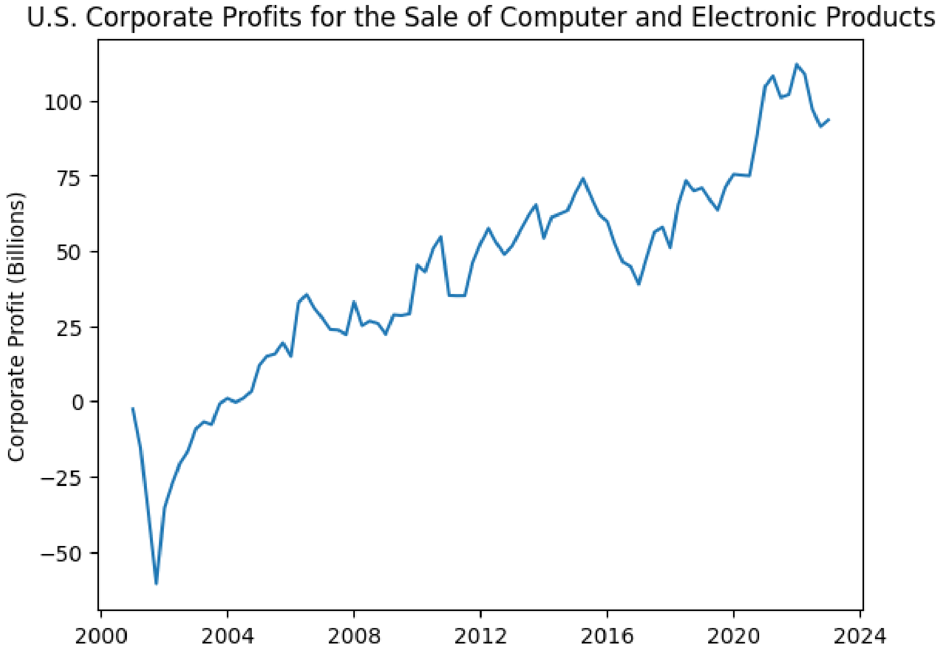

Figure 2.

The second dataset (DS2) comes from the General Administration of Customs of the People's Republic of China (GACC) Customs Statistics website, and contains data for electronic exports from China to the U.S. from 2015 through 2023 [5]. Figure 3 below illustrates this dataset.

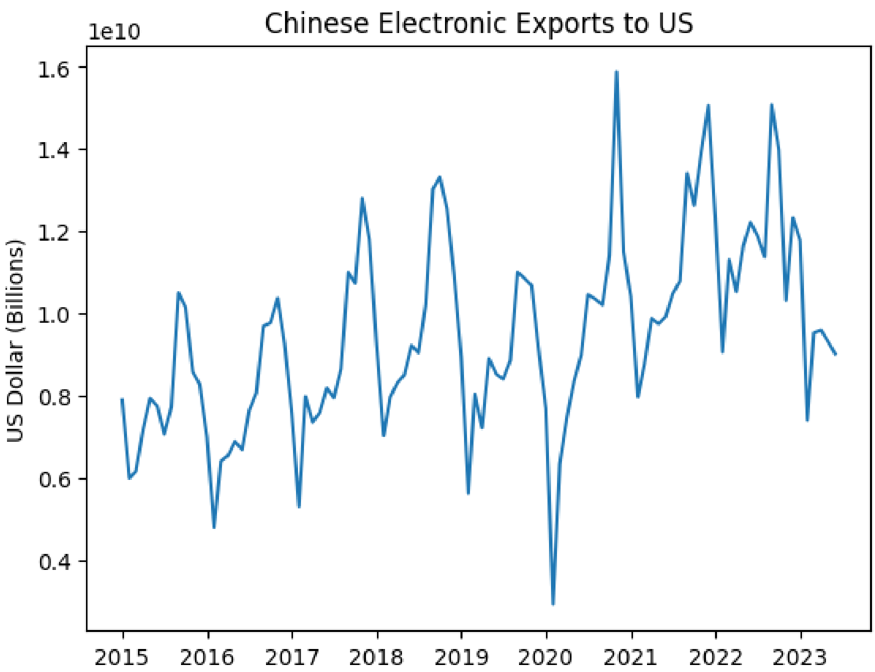

Figure 3.

The third and final dataset (DS3) comes from the Federal Reserve Bank of New York website, and measures the Global Supply Chain Pressure Index (GSCPI) from 1998 through 2023 [3]. Figure 4 below illustrates this dataset.

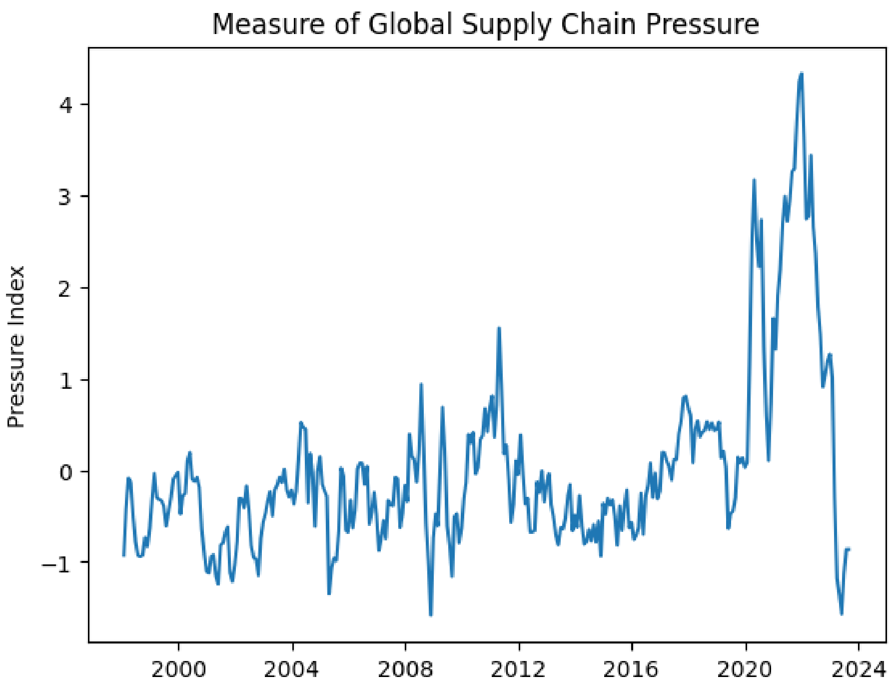

Figure 4.

2.2. Model Variables

We used the following Dependent and Explanatory variables found in our datasets to train our two AI models. Table 1 below illustrates these variables along with the data source for each.

Variable	Type	Source	Description
Growth Rate of U.S. Corporate Profits (electronic goods)	Dependent	DS1	Growth Rate of U.S. corporate profits on the sale of electronic goods. This is a calculated field equal to the growth rate.
Growth Rate of U.S. Imports from China (electronic goods)	Explanatory	DS2	Growth Rate of U.S. imports of Chinese electronic goods. This is a calculated field equal to the growth rate.
Inflection Dates	Explanatory	Manual	Dates of inflection points : • 7/1/2018 (start U.S.-China trade war) • 3/1/2020 (start of the COVID-19 pandemic) • 2/1/2021 (end of the COVID-19 pandemic) Binary Variable.
Supply Chain Pressure Index	Explanatory	DS3	Supply Chain Pressure Index

Table 1.

2.3. AI Modeling

For this project we chose to implement two neural network AI models (MLP and LSTM) to find which model better depicts the real-world behavior of U.S. corporate profits on electronic goods. Neural networks are made up of interconnected nodes, or neurons, that process information and learn from data.

A **Multi-Layer Perceptron (MLP) neural network** is a feedforward artificial neural network (ANN) that consists of an input layer, one or more hidden layers, and an output layer. Each layer is composed of neurons, which are simple processing units that apply a nonlinear activation function to their inputs. The connections between neurons in different layers are weighted, and these weights are adjusted during training to minimize the error between the network's predictions and the desired outputs.

A **Long Short-Term Memory (LSTM) neural network** is a type of recurrent neural network (RNN) that is specifically designed to learn long-term dependencies in sequential data. LSTM models are made up of special units called memory cells, which allow the model to store and retrieve information over long periods of time. A traditional RNN has a single hidden state that is passed through time. This can make it difficult for the network to learn long-term dependencies, as the hidden state can quickly forget important information. LSTMs address this problem by using three gates to control the flow of information into, out of, and through the memory cell. These three gates, described below, allow LSTMs to selectively remember and forget information over time, which makes them much better at learning long-term dependencies than traditional RNNs.

- Input gate: Controls how much new information is added to the memory cell.
- Output gate: Controls how much information from the memory cell is passed to the next layer of the network.
- Forget gate: Controls how much information is removed from the memory cell.

Table 2 shows similarities and differences between MLP and LSTM neural networks.

Characteristic	MLP Neural Network	LSTM Neural Network
Architecture	Feedforward	Recurrent
Type	Supervised learning model	Supervised learning model
Structure	Composed of layers of interconnected nodes	Composed of layers of LSTM units
Training	Trained on a dataset of labeled data	Trained on a dataset of labeled data
Inference	Takes a new input and produces an output	Takes a new input and produces an output, but can also retain information from previous inputs
Applications	Used for a variety of tasks, including classification, regression, and prediction	Used for a variety of tasks, including natural language processing, machine translation, and time series forecasting

Table 2.

3. Results

3.1. AI Model Scoring

All forecasts on the datasets were collected and an error score calculated to summarize the skill of each of our two AI models. The root mean squared error (RMSE) was used as it punishes large errors and results in a score that is in the same units as the forecast data, namely monthly revenue growth rate.

3.3 MLP Neural Network AI Model

For our MLP neural network AI model we implemented the **scikit-learn toolkit for Python** [6]. Specifically, we used the MLPRegressor object from this toolkit in our Python code.

The following illustrates the MLPRegressor class method in Python that lists all available parameters that can be used:

class **sklearn.neural_network.MLPRegressor**(*hidden_layer_sizes=(100,)*, *activation='relu'*, *, *solver='adam'*, *alpha=0.0001*, *batch_size='auto'*, *learning_rate='constant'*, *learning_rate_init=0.001*, *power_t=0.5*, *max_iter=200*, *shuffle=True*, *random_state=None*, *tol=0.0001*, *verbose=False*, *warm_start=False*, *momentum=0.9*, *nesterovs_momentum=True*, *early_stopping=False*, *validation_fraction=0.1*, *beta_1=0.9*, *beta_2=0.999*, *epsilon=1e-08*, *n_iter_no_change=10*, *max_fun=15000*)

We started with the default parameters for MLPRegressor to train our model with our datasets. As previously mentioned, our Explanatory variables included: Growth Rate of U.S. corporate profits (DS2), Inflection Dates (Calculated), and Supply Chain Pressure Index (DS3), while our Dependent variable was Growth Rate of U.S imports of electronic goods from China (DS1). After running many iterations of our code and trying many different parameter values and combinations, known as hyperparameter tuning, we arrived at the optimal parameter inputs to train our MLP neural network model as follows:

1) Set **Random State = 1.** Determines random number generation for weights and bias initialization, train-test split if early stopping is used, and batch sampling when solver='sgd' or 'adam'.
2) Set the Activation Type to: **logistic**. The logistic sigmoid function, returns f(x) = 1 / (1 + exp(-x))
3) Use **3 hidden layers**
4) Set the number of neurons for our hidden layers to high values of **1200, 1200, and 2000** respectively
5) Set **Max Iterations to: 1000**. Maximum number of iterations. The solver iterates until convergence (determined by 'tol') or this number of iterations.

Once our optimal parameters were found, we then ran three test cases to determine the importance of each of our chosen Explanatory variables to measure our MLP neural network's performance. Table 3 illustrates each test case and its corresponding score and root mean squared error (RMSE) value

Test Case: Explanatory Variable(s) Used	Score	RMSE Value
Growth Rate of U.S. corporate profits	49.02%	14.47
Growth Rate of U.S. corporate profits + Inflection Dates	52.15%	14.02
Growth Rate of U.S. corporate profits + Inflection Dates + Supply Chain Pressure Index	**97.52%**	**3.19**

Table 3.

Our MLP neural network AI model improved significantly from 52.15% to 97.52% when the **Supply Chain Pressure Index** was included, making it the most influential Explanatory variable in training our model to mimic the real-world behavior of U.S. corporate profits of electronic goods at a rate of **97.52%** accuracy.

Figure 4 shows the final results of our MLP neural network AI model, showing the actual vs. predicted results of growth rate in U.S. corporate profits on electronic goods as a function of time.

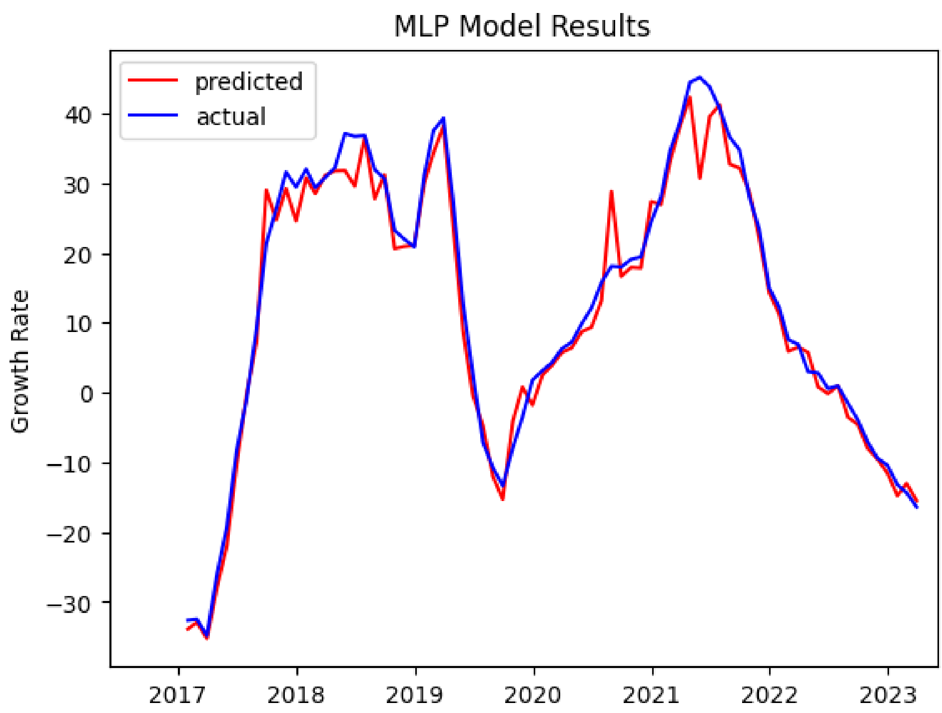

Figure 4.

3.3. LSTM Neural Network AI Model

For our LSTM neural network AI model we implemented the **TensorFlow machine learning toolset for Python** [7]. Specifically, we used the [Sequential LSTM model]() from this toolkit in our Python code.

The TensorFlow Sequential model is a LSTM neural network AI model that is appropriate for a plain stack of layers where each layer has exactly one input tensor and one output tensor. It consists of defining layers in which to train an AI model.

You can create a Sequential model by passing a list of layers to the Sequential constructor:

```
model = keras.Sequential(
    [
    layers.Dense(2, activation="relu"),
    layers.Dense(3, activation="relu"),
    layers.Dense(4),
    ]
)
```

We started with the default parameters for our Sequential object to train our LSTM model with our datasets. As previously mentioned, our Explanatory variables included: Growth Rate of U.S. corporate profits (DS2), Inflection Dates (Calculated), and Supply Chain Pressure Index (DS3), while our Dependent variable was Growth Rate of U.S imports of electronic goods from China (DS1). After running many iterations of our code and trying many different parameter values and combinations, known as hyperparameter tuning, we arrived at the optimal parameter inputs to train our LSTM code as follows:

1) Use **one LSTM Layer with 280 neurons and Activation Type = sigmoid**
2) Use **five Dense Layers, each with 125 neurons and Activation Type = linear**
3) Use **1 Dropout Layer, with rate of 0.65** to address overfitting
4) Use a **final Dense Layer with 1 neuron and Activation Type = linear.** A final dense layer with one neuron in an LSTM model is used for binary classification tasks.
5) Set l**oss = mean_squared_error and optimizer = adam** for the compile method

Once our optimal parameters were found, we then ran three test cases to determine the importance of each of our chosen Explanatory variables to measure our LSTM neural network's performance. Table 4 illustrates each test case and its corresponding score and root mean squared error (RMSE) value.

Test Case: Explanatory Variable(s) Used	Score	RMSE Value
Growth Rate of U.S. corporate profits	4.14%	20.68
Growth Rate of U.S. corporate profits + Inflection Dates	24.50%	22.61
Growth Rate of U.S. corporate profits + Inflection Dates + Supply Chain Pressure Index	**50.67%**	**24.88**

Table 4.

Our LSTM neural network AI model achieved a 50.67% accuracy score and did not perform as well as our MLP neural network AI model which achieved a 97.52% accuracy score.

Figure 5 shows the final results of our LSTM neural network AI model, showing the actual vs. predicted results of growth rate in U.S. corporate profits on electronic goods as a function of time.

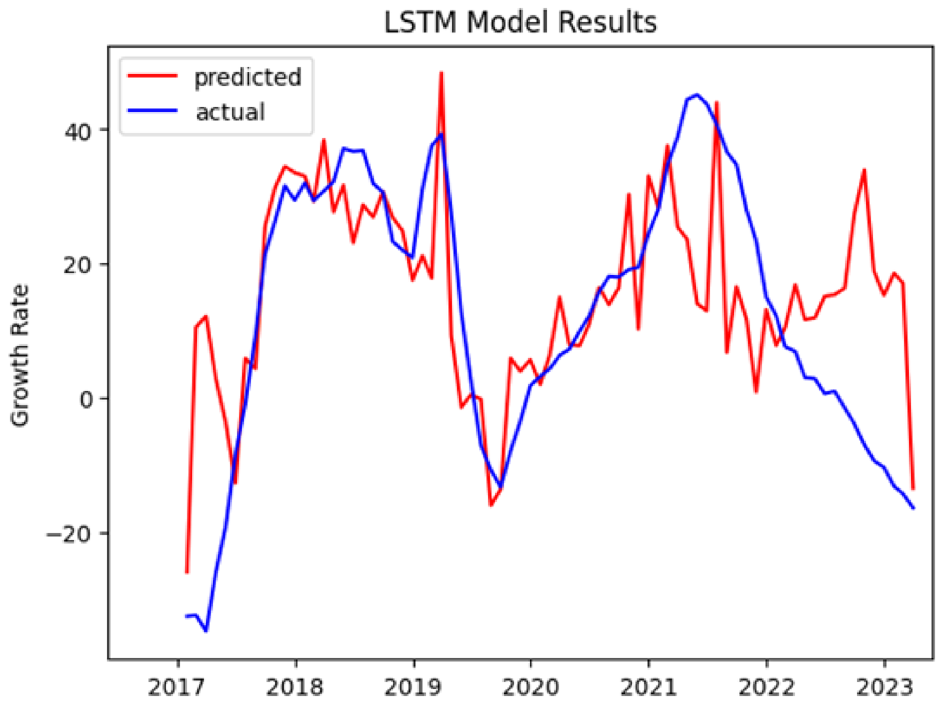

Figure 5.

4. Discussion and Conclusion

4.1. Major Findings

- Our MLP neural network AI model performed better than our LSTM neural network AI model.
- Our MLP neural network AI model performed at a 97.52% success rate of repeating real-world outcomes, while our LSTM neural network AI model was only able to achieve a 50.67% success rate.

4.2. Findings Related to Existing Research

- Our findings show that the datasets (and Explanatory variables that we chose), along with hyperparameter tuning of our MLP neural network, did indeed allow us to come very close to real-world outcomes with our AI predictive modeling.

4.3. Significance of Results

- Our findings show that Supply Chain Pressure is the single largest factor impacting U.S. corporate profits on the sale of electronic goods.
- Our inflection dates also significantly contributed to changes in our datasets including the start of the 2018 trade war (7/1/2018) as well as the start of COVID-19 (3/1/2020) and the end of COVID-19 (2/1/2021). All inflection dates played a significant role in the trajectory of U.S. corporate profits on the sale of electronic goods.
- MLP neural networks outperform LSTM neural networks when the data is non-sequential. LSTMs are designed to learn from sequential data, so they are not well suited for tasks where the data is not in a specific order. For this specific research, even though most of our datasets represent sequential time series data, our non-sequential supply chain pressure index dataset caused our MLP model to perform better than our LSTM model against all datasets.

4.4. Limitations and Future Directions

- We could only train our two AI models with data from January 2017 through the end of Q1 2023 due to data limitations on data gathering of Chinese exports of electronic goods to the U.S. In the future, we would like to re-train our models with updated Chinese export data to the U.S. from Q2 through the remainder of 2023 to see how our models perform.
- We would like to have done more hyperparameter tuning of our LSTM model to achieve better results.
- The CHIPS and Science Act is a U.S. federal statute enacted by the 117th United States Congress and signed into law by President Joe Biden on August 9, 2022. The act provides roughly $280 billion in new funding to boost domestic research and manufacturing of semiconductors in the United States [8]. In the future, we would like to incorporate the Chips Act date as an additional Explanatory variable to further train our two AI models to match real-world outcomes.

Acknowledgments

I would like to sincerely thank Ana Sofia Munoz Valadez for guiding me through this project as my mentor. I am also thankful to InSprit AI for including me in this highly valuable program, allowing students like myself to learn real-world AI software solutions using Python and the Google Colab development environment.

References

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GitHub Repository

The GitHub Repository for this project which includes all code, datasets, and results can be found here.
https://github.com/WilliamKrofchik/InSpiritAI-Neural-Networks-US-Corporate-Profits