Forecasting Unemployment Rates Using a Combined ARIMA and LSTM Approach

MSc Research Project
Msc Data Analytics

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MSc Project Submission Sheet

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AI Acknowledgement Supplement

1 MSc Research Project

Your Name/Student Number	Course	Date
Kushagra Airen	Msc Data Analytics	12-08-2024

This section is a supplement to the main assignment, to be used if AI was used in any capacity in the creation of your assignment; if you have queries about how to do this, please contact your lecturer. For an example of how to fill these sections out, please click here.

2 AI Acknowledgment

This section acknowledges the AI tools that were utilized in the process of completing this assignment.

Tool Name	Brief Description	Link to tool
ChatGPT	To get ideas on the title	https://chatgpt.com/

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ChatGPT	
Used for title suggestions	
Give title suggestions	Here are some title suggestions

4 Evidence of AI Usage

ChatGPT 4

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Here are some title suggestions based on your research project:

1. "Enhancing Unemployment Forecasting: A Hybrid ARIMA-LSTM Approach"
2. "Predicting Unemployment Trends: Integrating Statistical and Deep Learning Models"
3. "A Hybrid Machine Learning Model for Accurate Unemployment Rate Prediction"
4. "Unemployment Rate Forecasting: Combining ARIMA and LSTM for Improved Accuracy"
5. "Advancing Economic Forecasting: A Hybrid Approach to Unemployment Prediction"
6. "Dynamic Unemployment Prediction Using ARIMA and LSTM Models"
7. "Hybrid ARIMA-LSTM Model for Forecasting U.S. Unemployment Rates"
8. "Combining ARIMA and LSTM for Robust Unemployment Rate Prediction"
9. "A Comparative Study of ARIMA, LSTM, Hybrid Models in Unemployment Rate Forecasting"

Forecasting Unemployment Rates Using a Combined ARIMA and LSTM Approach

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Abstract

Predicting unemployment involves using historical data and macroeconomic factors to estimate the value of the number of unemployed people as a percentage of the labor force. This study proposes a hybrid approach of combining the strengths of a statistical model like ARIMA and a deep learning model like LSTM to accurately predict the unemployment rate especially in economic crisis like COVID-19 pandemic. A combination of financial indicators of United States datasets, spanning from 1979 to 2023 are used to train the model to predict unemployment rate. Along with ARIMA-LSTM hybrid model, standalone models of ARIMA and LSTM were also implemented and evaluated using the performance metrics, in which the standalone LSTM model has outperformed the hybrid model with the MAE of 0.43. The objective of this research also aligns with the United Nations Sustainable Development Goal 8 since by predicting unemployment this study will aid in inclusive and sustainable economic growth and ensure productive employment and decent work for all.

Keywords: ARIMA-LSTM; hyperparameter tuning; LSTM; unemployment; economic crisis

1 Introduction

Predicting the unemployment rate is crucial for the economy and social well-being of a country, as it helps in formulating economic policies, ensuring social stability and individual well-being. Traditional methods used in predicting unemployment such as econometric model and single-variable time series analyses, have often failed in capturing the complex nature of unemployment dynamics. For instance, traditional models face limitations in handling non-linear relationships and incorporating diverse economic indicators, leading to less accurate predictions. On the other hand, advanced deep learning models though powerful, often had difficulties in accurately capturing linear trends. Additionally, the author highlights the necessity for more comprehensive models that can adapt to changing economic conditions and integration of multiple variables for better accuracy (Mero et. al, 2024) [1]. While hybrid models have been employed in previous studies to predict unemployment rates, there remains room for improvement in their performance. Thus, utilizing both standard statistical approaches and sophisticated deep neural networks, this work is intended to help promoting the improvement of unemployment rate prediction models that would be useful for policy makers in devising future laws and policies.

Research Question: To what extent can a hybrid ARIMA-LSTM model accurately predict unemployment rates specifically during economic downturns?

The aim of this research is to predict the unemployment rate. To address the research question, the following specific sets of research objectives were derived:

1. Implement standalone models of ARIMA on the historical unemployment rate and LSTM on macroeconomic factors (Inflation, GDP and Stock Market Prices).
2. Design a hybrid model framework incorporating statistical model (ARIMA) and deep learning (LSTM) techniques.
3. Implement the hybrid model framework for prediction of unemployment rate.
4. Evaluate the model performance using metrics such as MAE, MSE and MAPE.

The major contribution of this research is a novel hybrid unemployment forecasting framework that integrates a statistical model like ARIMA with a deep learning model like LSTM to forecast unemployment rate of United States of America including multiple economic fluctuations (1990 Oil crisis, 2000 dot-com bubble, 2008 Great Recession and 2020 COVID-19 pandemic). The hybrid model is aimed at combining the strengths of both ARIMA and LSTM, in which the linear trends and the seasonal trends are handled by the ARIMA while the LSTM handles the non-linear trends and other complex dependencies. To accomplish this, the study aims to incorporate various economic indicators including GDP, inflation rate and stock market prices and in addition to lag features of 6 and 12 months to improve the unemployment prediction's precision and dependability. The proposed hybrid ARIMA-LSTM model will then be compared to the performance of the standalone ARIMA model and the LSTM model.

This paper is organized into several key sections, following introduction literature review is discussed in section 2, which describes the previous findings of this subject, by comparing with this research. Section 3 discusses the methodological approach and the implementation of the models for the research. The evaluation of the results is discussed in Section 4. Section 5 presents the conclusion derived from the study and discuses the future work.

2 Related Work

This literature review will explore previous research models, evaluate the effectiveness of different approaches and identify gaps in existing research which can be addressed in this research.

The quality and granularity of the dataset used greatly affects the model's performance. For example, Bokanyi, E. et al. demonstrated how social media like twitter can be leveraged to understand economic trends by analyzing 63 million tweets of United States of year 2014 [15]. Similarly, Ryu utilized news articles, blogs and tweets to predict unemployment in South Korea, using models such as ARIMAX and ARX by combining sentiment analysis and traditional statistics methods [16]. Likewise, D'Amuri, F. and Marcucci, J [14] utilized Google Index (GI) job search to predict real time unemployment and compared it with initial claims from employers in the United States. They suggested the use of this model for long term forecasts, especially during economic downturns, due to its stability [14]. However, using social media content may introduce biases in the results, as they depend heavily on the regional contexts and primarily reflect opinions of younger age groups, who are most active on the social media.

Over the years, various concepts have been introduced that showcase the relationship between economic indicators and the unemployment rate. For example, Qin justified the Phillips Curve, which illustrates the inverse relationship between inflation and unemployment [9]. Beyond inflation, GDP has also been used to predict the unemployment rate, Zhu demonstrated a similar inverse relationship between GDP and unemployment [10]. In addition, stock market prices also has an impact on unemployment rate, as Chi stated that the news about unemployment significantly affects stock market volatility [2]. Similarly, Gonzalo & Taamouti confirmed that stock market prices rise when an increase in the unemployment rate is expected [4]. Both Qin [9] and Zhu [10] suggest the use of multivariate analysis to enhance the accuracy of unemployment predictions.

Authors like Sun and Huruta have demonstrated the use of ARIMA model for predicting unemployment rates, which has been widely used for time series analysis by many other researchers. [8], [5]. For instance, Huruta [5] had successfully forecasted the unemployment rate of Indonesia, achieving a Mean Absolute Percentage Error (MAPE) of 9.56%, while Sun [8] used global unemployment data from the world bank to achieve a MAPE of 2.103% [3]. Additionally, the ARIMA model has limitations, particularly in handling non-stationary data and incorporating other macroeconomic indicators. Due to these limitations, ARIMA models need to be complemented with other models to enhance their performance [4].

Shi et al. [13 employed an ARIMA-ARNN model to predict the impact of COVID-19 pandemic on the unemployment rates of developing South Asian countries, they achieved superior predictive accuracy over standalone models like ARIMA, SVM and ANN. Their results indicates that hybrid models can better handle non-stationary data, making them highly effective for forecasting in volatile economic conditions.

Similarly, Ahmad et al. [17] investigated Hybrid models such as ARIMA-ARNN, ARIMA-ANN and ARIMA-SVM were employed on unemployment data. The neural network models or SVM captured the nonlinear trends in the data, whereas the ARIMA model captured the linear trends. Their results showed that the ARIMA-ARNN model performed best for France, Belgium, Turkey and Germany, while the ARIMA-SVM model was more effective for Italy and Spain. These results indicate that the choice of the model may vary with the region and the characteristics of the unemployment rate.

Yurtsever M [12] proposed a hybrid approach by combining (LSTM) and (GRU) methods for forecasting unemployment rates of United States, United Kingdom, France and Italy. The model architecture consists of an LSTM layer with 128 hidden neurons, a GRU layer with 64 hidden neurons, and a dense layer with one output neuron. The results of the study showed that LSTM-GRU model performed better for all countries except Italy, where Standalone GRU model outperformed.

Finally, Mero et al. [1] introduced the GA-LSTM approach which integrates (GA) and (RNN) to predict Ecuador's unemployment rate. The study utilized factors like minimum wage, GDP, and Gross Fixed Capital Formation (GFCF), along with unemployment rate. Initially, the genetic algorithm was executed to optimize parameters of LSTM model. Then the LSTM model was employed on the optimized parameters to enhance model performance. The results showed that the GA-LSTM model outperformed other models employed such as BilSTM and GRU, with a Mean Squared Error (MSE) of 0.052 and MAPE of 3.797 %, indicating the effectiveness of the model. However, this outstanding MSE value was obtained on pre-COVID-19 data, indicating uncertainty in the model's performance under sudden economic changes.

Table 1: Summary of Previous Research's applied on Unemployment Data

Author's	Dataset	Methodology and Model's Applied	Results and Key Findings
Bokányi, E., Lábszki, Z. and Vattay, G. (2017) [15]	63 million tweets from the United States (2014)	Leveraged social media data, ARIMAX and ARX models, employed sentiment analysis.	Showed how Twitter data can predict economic trends, highlighted potential biases due to regional contexts.
Ryu, P.-M. (2018) [16]	News articles, blogs, and tweets (South Korea)	ARIMAX and ARX models; sentiment analysis	Demonstrated effective unemployment prediction using a combination of sentiment analysis and traditional methods.
D'Amuri, F. and Marcucci, J. (2017) [14]	Google job search index data and initial claims (United States, 2004-2014	AR models augmented with Google Index (GI) and initial claims data; BIC for model selection	Found that Google-based models outperform traditional models in predicting unemployment, especially during the Great Recession; highlighted GI's strength in capturing early job search behavior.
Qin, Y. (2020) [9]	U.S. unemployment and inflation data (Q1 1962 - Q1 2020)	VAR (Vector Autoregression) model, Granger Causality Tests, Impulse Response Analysis	Confirmed the Phillips Curve's relevance in both short and long terms; identified unemployment as a predictor for inflation, but not vice versa.
Zhu, Y. (2023) [10]	U.S. GDP, Inflation, and Unemployment data (Q1 2012 - Q1 2022)	VAR (Vector Autoregression) model, Granger Causality Tests, Impulse Response Analysis	Demonstrated the complex relationships between GDP, inflation, and unemployment; found that GDP and unemployment can predict inflation, and GDP and unemployment have a bidirectional causality.
Chi, D. (2021) [2]	U.S. Unemployment rate data from U.S. Bureau of Labor Statistics and stock market data from Yahoo Finance (2000-2020)	OLS Regression model, Robustness checks through trading volumes and shorter time windows	Found that surprise in unemployment rate announcements leads to increased market volatility (VIX) but has a less pronounced effect on stock market returns

			(SPY).
Sun, F. (2023) [8]	Global unemployment data from World Bank (1991-2022)	ARIMA model, Forecasting, and Analysis using R	RMSE of 0.172 and MAPE of 2.103%; highlighted ARIMA's limitations with non-stationary data and economic shocks.
Huruta, A. (2024) [5]	Unemployment data from Indonesia (1990-2022)	ARIMA model	Obtained MAPE of 9.56%; highlighted ARIMA's reliance on historical data pattern and pointed out limitations, particularly in long-term demographic trends.
Shi, L., Khan, Y.A. and Tian, M.-W. (2022) [13]	A Hybrid Approach; Unemployment data from South Asian countries	ARIMA, ANN, SVM, ARNN, ARIMA-ARNN, ARIMA-ANN, and ARIMA-SVM.	Hybrid ARIMA-ARNN achieved superior predictive accuracy over standalone models
Ahmad, M., Khan, Y.A., Jiang, C., Kazmi, S.J.H. and Abbas, S.Z. (2021) [17]	Unemployment data of France, Belgium, Turkey, Italy and Germany	ARIMA, ARNN, ANN, SVM, ARIMA-ARNN, ARIMA-ANN, and ARIMA-SVM.	Found ARIMA-ARNN best for France, Belgium, Turkey, and Germany; ARIMA-SVM more effective for Italy and Spain.
Yurtsever, M. (2023) [12]	Monthly unemployment data (US, UK, France, Italy, 1983-2022)	Hybrid LSTM-GRU model	LSTM-GRU outperformed in all countries except Italy; highlighted effectiveness of hybrid models with MAPE values of 3.91% for the US, 4.66% for the UK, 1.10% for France, and 2.27% for Italy.
Mero, K., Salgado, N., Meza, J., Pacheco-Delgado, J. and Ventura, S. (2024) [1]	Unemployment data from Ecuador (2002-2019)	BiLSTM, GRU, GA-LSTM model; Genetic Algorithm for optimization	GA-LSTM outperformed BiLSTM and GRU with MSE of 0.052 and MAPE of 3.797%

In Conclusion, work highlights the importance of high-quality datasets and advance modelling techniques for accurately predicting unemployment rate. Previous research indicated that though ARIMA model was widely used but has limitations in handling non-stationary data and economic downturns like COVID-19, where a more robust approach is needed. Thus, the latter approaches complemented ARIMA with other models (ARIMA-ARNN, ARIMA-ANN and ARIMA-SVM) so that the non-linear patterns can be captured, which resulted in improved performance. However, there is a need to train the model in sudden economic shocks which the latter lacks. In addition, the combination of LSTM and a statistical analysis model like ARIMA can be explored in predicting unemployment. This research proposes a hybrid machine learning framework that combines ARIMA's ability to capture linear patterns and LSTM's ability to capture non-linear patterns and temporal dependencies in the unemployment data. Additionally, this research will also include multivariate analysis incorporating inflation, GDP and stock market prices and will explore their impact on the unemployment rate. This hybrid method is expected to adapt better to dynamic economic conditions and address the limitations of the state of the art, thus offering better prediction for economists and policymakers.

3 Research Methodology

For applying the proposed model, a comprehensive research methodology has been applied as shown in figure 1. It consists of 4 key sections namely data gathering, data preprocessing, data modelling and performance evaluation.

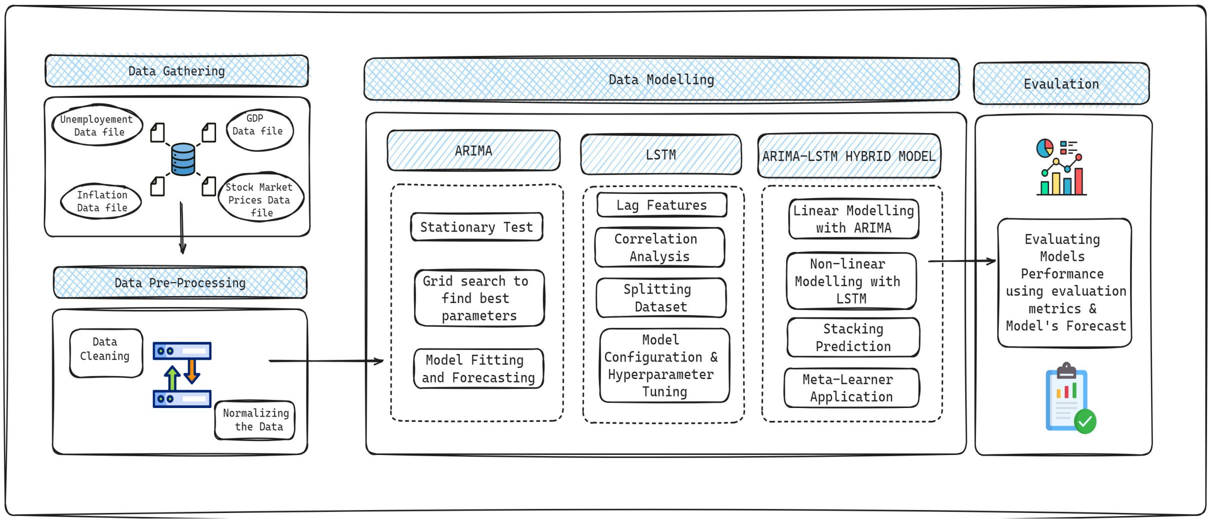

Figure 1: Research Methodology

3.1 Data Gathering

For this research, the datasets of the four economic indicators were obtained from Kaggle, an open-source platform. This dataset belongs to United States of America and provide a broad view of the economic indicators used for predicting the unemployment rate. Below table contains the details of the economic indicator csv files used.

Table 2: Details of the data files

Economic Indicator	File Name	Columns	Timeframe	Frequency
Unemployment Rate	Unemployment Rate.csv	DATE, UNRATE	January 1948 - April 2023	Monthly
GDP	Gross Domestic Product.csv	DATE, GDP	Q1 1947 - Q1 2023	Quarterly
Inflation Rate	US_inflation_rates.csv	Date, Inflation	February 1947	Monthly

		Rate	- June 2023	
S&P 500 Index	SPX500.csv	Date, Price, Open, High, Low, Volume, Change %	December 1979 - May 2023	Daily (irregular)

All these economic indicators files were loaded, and the necessary data preprocessing steps were implemented, which are explained in the next subsection.

3.2 Data Preprocessing

After loading the CSV files, data preprocessing is required to make the data ready for modeling. In this, steps like data cleaning and normalization were performed. The following steps were taken for data cleaning.

- To ensure consistency, firstly the date column in all the datasets were converted into a standard datetime format and will be used as index column to ease manipulation. Since the S&P 500 Index dataset was from 1979 so all the other datasets were filtered for entries starting from 1st January 1979.
- The monthly inflation rate was calculated using the percentage change method in the Consumer Price Index (CPI) and then resampled into monthly frequency to ensure no missing values are present. Also, the first row of the inflation dataset is removed since it contains a NaN value.
- In the S&P 500 Index dataset, columns Price, Open, High, Low, and Volume were dropped and only Change % is retained, which will be used for the analysis. Also, the Change % column is converted into a numeric type from a string type. Then the monthly mean was calculated to convert the daily data into monthly.
- Interpolation method was applied on the GDP data to convert quarterly data into monthly. This was achieved using forward filling of the values in the dataset, so that every month has a value.
- After this, the datasets were merged using date column and were checked for any null or missing values.

The final merged dataset contains 518 rows and was from 31st December 1979 to 1st January 2023. Figure 2 showcases the unemployment rate over time. In which the peak represents the economic downturns such as the global recession and the COVID-19 pandemic.

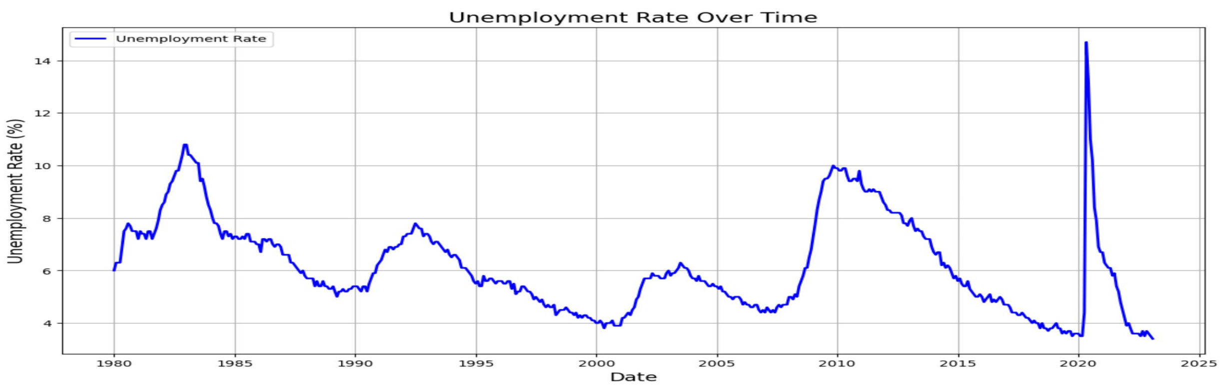

Figure 2: Unemployment Rate over Time

After that, normalization was applied on the unemployment rate using MinMaxScaler method to scale the values, which will help increase the efficiency of ARIMA and LSTM models.

3.3 Data Modelling

This section explains the theoretical background and implementation of three approaches ARIMA, LSTM and a hybrid ARIMA-LSTM model. Each model has distinct abilities in leveraging unique aspects of data to predict unemployment rate.

3.3.1 ARIMA Model

ARIMA (AutoRegressive Integrated Moving Average) is a forecasting model used particularly for time series data. The model is structured as ARIMA (p, d, q) where the parameters explain the order of the model's key components:

- **AR (p) AutoRegression:** A regression model which utilizes the relation between previous observations and the current observation where p represents the number of previous observations included in the model also referred as the lag order.
- **I (d) Integration:** This component explains the differencing required to make the time series stationary where d represents the number of times differencing was done to achieve stationarity.
- **MA (q) Moving Average:** It models the relationship between an observation and residual error from a moving average model implemented on previous observations, where q represents the size of the moving average window.

Before applying ARIMA model it is important to check the stationarity of the time series for which Augmented Dicky-Fuller (ADF) test is used commonly. This test will help ensure if the statistical properties (like mean and variance) are constant over time. If the p-value from the test is below 0.05 then the series is assumed to be stationary thus differencing is not needed. Based on the results of stationarity check the value of d can be determined, but for finding the optimal value of p and q other methods need to be employed. One such method is grid search, in which the optimal parameters are search using a for loop for a defined range of values and evaluating performance for each combination using a selected performance metrics, such as Mean Squared Error (MSE) or Mean absolute Error (MAE). Using AD-fuller test and grid search for identifying parameters is very useful since it reduces the risk of overfitting of the model. Employing such methods is crucial to find the optimal orders for implementing robust ARIMA model.

Implementation of ARIMA model.

- **Stationarity Test:** ADF test was implemented to check the stationarity of unemployment rate data. This test resulted in ADF statistic of approximately -2.92 and p-value of 0.0427, indicating that the series is stationary at 5% significant level and the value of d can be selected as 0.
- **Splitting Dataset and Grid Search:** The dataset is splitted into training and testing set with 80% training data and 20% testing data. After splitting the dataset, the grid search is applied on the training data and for both the parameters p and q the values varied from 0 to 4. Then the ARIMA model was trained for each combination of parameters and MSE was calculated to evaluate the performance. After, evaluation the parameter combination

of (2, 0, 4) was selected as the optimal parameters since it has given the lowest MSE among all.

- **Model Fitting and Forecasting:** The ARIMA model was then fitted on the training set using the optimal order (2, 0, 4). After which the fitted model was used to forecast unemployment rate of testing set using the predict function, which can then be compared to the actual values to asses the performance of the model. Then the fitted model was used to forecast unemployment rate using the predict function, which can be compared to the actual values to assess the model's performance.

3.3.2 LSTM Model

Long Short-Term Memory (LSTM) model is a specialized form of Recurrent Neural Networks (RNNs) model, which is designed to counter the vanishing gradient limitation of RNN. While traditional RNN models struggle with learning long term dependencies LSTM are quite capable of doing that. LSTM introduces a memory cell which helps the model to retain the information over longer periods. This is controlled through a set of gates:

- **Input Gate:** Controls the information to be added to the memory cell.
- **Forget Gate:** Determines what information should be removed from the memory cell.
- **Output Gate:** Decides what information from the memory cell should be passed to the output.

The above architecture helps the model to learn from short-term and long-term dependency making it efficient for time series forecasting where the model selectively decides in retaining and discarding information as it flows through the network. Additionally, LSTMs have a hidden state for short term dependency, dynamically updating based on the input, the previous hidden state and the current output state.

In LSTM model, input data is typically structured as sequence, where each sequence consists of a specified number of time steps. The time step defines how many previous number of data points to be used to predict the next value. Choosing a time step is important as it avoids the risk of the model getting overloaded with unnecessary information. After choosing the appropriate time step, model architecture needs to be defined which consists of multiple layers:

- **LSTM Layers:** The LSTM layers help the model learn complex patterns in the data. For instance, the first layer might learn short-term trends while the subsequent layer learns the long-term trends. Like this, these layers are used to furnish the input and pass on the information to the next layer. Each layer is configured with a specific number of units which controls the dimensionality of the output space. These units can be optimized further using hyperparameter tuning to produce the best results.
- **Dropout Layers:** During training, the dropout layer updates a fraction of the input unit as 0, this regularization helps in reducing the risk of model getting overfitted.
- **Dense Layer:** Dense layer is the output layer and produces the model's output, which is the unemployment rate.

In addition to model parameters, LSTM models also involve hyperparameters, such as the number of units and learning rate. These parameters are usually fixed before the model and express the complexity of the model. These hyperparameter can be tuned by a process called hyperparameter tuning, which is selecting their optimal values so that the model performance can be maximized.

Implementation of LSTM model.

- **Lag Features:** 6 months and 12 months lag features were added to the dataset to understand the temporal patterns and dependencies in the data. These features will help the model understand the past unemployment rate while predicting.
- **Correlation Analysis:** Pearson correlation was performed on the features to explore the relationships between the features. This method returns a correlation coefficient which ranges from -1 to 1, representing the measure of linear relationship between two variables. Figure 3 contains the correlation matrix obtained from the analysis. Based on the matrix, both UNRATE_LAG_6 and UNRATE_LAG_12 show a strong positive correlation with the target variable unemployment (UNRATE) whereas GDP and inflation show moderate and weak negative correlation with unemployment. Also, the change % (S&P Index) shows a weak positive correlation not indicating a significant impact on the unemployment rate. Based on the analysis, no features were dropped from the dataset, and all are used in the model.

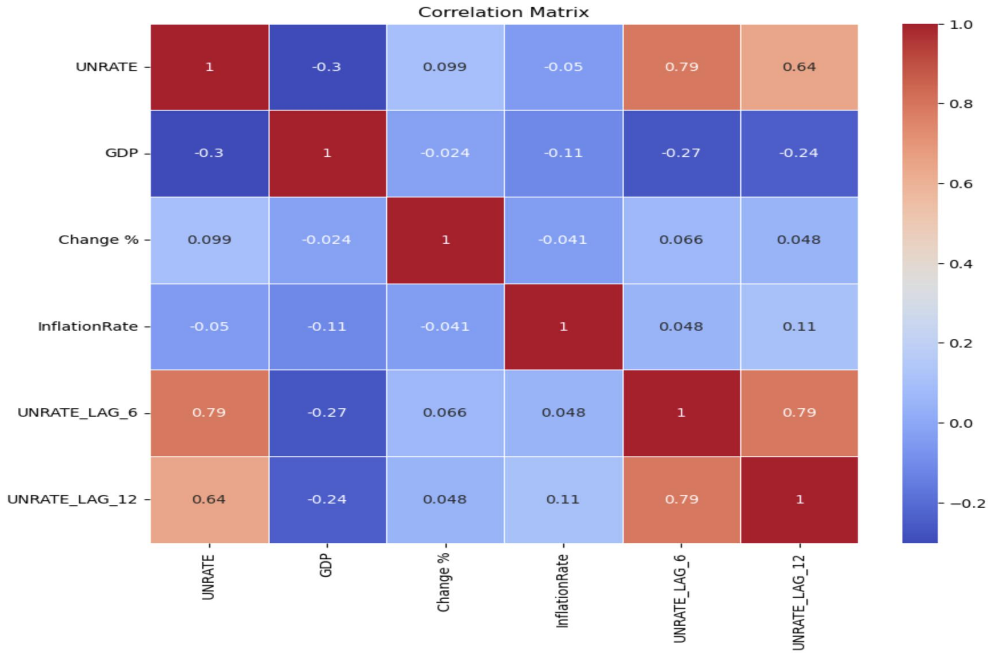

Figure 3: Correlation Matrix

- **Splitting Dataset:** The dataset is then splitted into training and testing set, with 80% data in the training set and 20 % in the testing set. Also, the time step for LSTM model was chosen as 10, which indicates that the model will use the previous 10 values to predict the next value.
- **Model Configuration and Hyperparameter Tuning:** Table 3 contains the configuration used to build the model. The model contains 2 layers each followed by a dropout layer. Further, hyperparameters such as number of units and learning rate were tuned using Keras tuner. In which the RandomSearch tuner was used to randomly explore different combinations of hyperparameters. In this max_trials was selected as 10, which means the tuner runs upto maximum of 10 trials of different models, executing

each trial twice and is evaluating each performance based on the validation loss (val_loss).

Table 3: Configuration of LSTM Model

Component	Details
Input Features	UNRATE_LAG_6, UNRATE_LAG_12, GDP, Inflation Rate, S&P 500 Change %
Normalization	MinMaxScaler (scaled to a range of 0 to 1)
Time Steps	10
LSTM Layer 1	128 units, return_sequences=True
Dropout Layer 1	Dropout rate: 0.1
LSTM Layer 2	80 units, return_sequences=False
Dropout Layer 2	Dropout rate: 0.1
Dense Layer	1 unit
Activation Function	Linear (default activation function for the output layer)
Optimizer	Adam (learning rate: 0.01)
Loss Function	Mean Squared Error (MSE)
Batch Size	5
Epochs	10
Hyperparameter Tuning	● Layer 1: Number of units in the first LSTM layer (tuned between 32 and 128 units, in steps of 16). ● Layer 2: Number of units in the second LSTM layer (tuned between 32 and 128 units, in steps of 16). ● Learning Rate: Learning rate for the Adam optimizer (tuned among 1e-2, 1e-3, 1e-4).

- **Model Training:** The LSTM model was then trained on the training set and evaluated on the test set using model prediction and performance metrics.

3.3.3 ARIMA-LSTM Hybrid Model

The proposed hybrid model is introduced to combine the strengths of both ARIMA and LSTM model. The ARIMA model can capture the linear patterns and trends in the time series data, while the LSTM model can capture non-linear patterns and complex dependencies that ARIMA might not capture. ARIMA works well where the future values are linearly dependent on the past values, exhibiting a clear autocorrelation structure where as LSTMs are used when the data exhibit complex patterns and the time series data has non-linearities in it. The idea behind the ARIMA-LSTM hybrid model is to decompose the time series into linear and non-linear components where ARIMA can model the linear component, and LSTM can model the non-linear component. Below table gives a detailed summary of the working of the hybrid model.

Table 4: Working of ARIMA-LSTM Hybrid model

Step	Description
Step 1: ARIMA Model	Apply ARIMA model on the linear components of the time series data.
Step 2: LSTM Model	Apply LSTM model on the time series data to capture non-linear components.
Step 3: Stacking Predictions	Combine the ARIMA and LSTM predictions as features for the meta-learner (Linear Regression).
Step 4: Meta-Learner Application	Use the Linear Regression model to combine ARIMA and LSTM predictions for the final forecast.

As explained in the above table the hybrid model leverages the strengths of both ARIMA and LSTM model to forecast for a time series data and is capable of producing a more robust output than the standalone models.

Implementation of ARIMA-LSTM hybrid model.

- **Linear Modelling with ARIMA:** At first the ARIMA model was applied on the unemployment rate data using the optimal parameters identified earlier (2, 0, 4). The ARIMA model was then used to make predictions for the test set which represents linear components in the time series data.
- **Non-linear Modelling with LSTM:** Then, the LSTM model was also applied on the unemployment rate data to capture non-linear patterns that ARIMA model might not capture. The LSTM model was applied on the scaled data of unemployment rate and later optimized with hyperparameter tuning.
- **Stacking Predictions:** ARIMA and LSTM model prediction were combined to be stacked as single feature set. The process involves adjusting the ARIMA predictions to match the LSTM model’s time window. It was done because of the number of predictions in ARIMA is 10 more than the LSTM, since the LSTM has a time step of 10. The feature set was then splitted into training and test set.
- **Meta-Learner Application:** Finally, the Linear Regression model was implemented on the training set to learn the optimal weighting and generate the final predictions of the hybrid model.

3.4 Performance Evaluation

For evaluating the three models applied in the research which are ARIMA, LSTM and ARIMA-LSTM, the criteria defined by Chung and Shin (2018) and Mero et al. (2023) were used, which consist of Mean Squared Error (MSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) [18], [1]. These measures can be calculated as follows:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| * 100$$

where y_i is actual value, $\hat{y}_i$ is the predicted value, n is the number of predictions and residual error is $y_i - \hat{y}_i$.

For comprehensively evaluating the models, the combination of MSE, MAE and MAPE was chosen. MSE maximizes the large errors, it ensures that the model's predictions are accurate on average and is consistent across all data points. However, MAE does not square the error, thus providing a balanced view of prediction accuracy. MAE gives average prediction error on the same units as the data. Additionally, MAPE is defined as the average of absolute percentage error between the predicted values and the observed values. It is used as it provides a measure of prediction accuracy in percentage terms and as in this research, the relative variations is more important than absolute variations [19]. The closer the values of MSE, MAE and MAPE are to zero, the more accurate the model will be.

4 Results and Discussions

4.1 Experiment 1- ARIMA Model

Below is the table containing the performance metrics of ARIMA model.

Table 5: Performance metrics of ARIMA model

Performance Metrics	Value
MSE	3.95
MAE	1.49
MAPE	0.3277

The findings indicate that the ARIMA model has not performed well on the historical unemployment rate data. The relatively high MSE of 3.95 suggests that the model struggles in minimizing large errors, especially when the data includes economic downturns like COVID-19. Similarly, the MAE of 1.49 indicates that the average difference between the predicted and actual unemployment rates is approximately 1.5. The MAPE of 32.77% (0.3277) further demonstrates that the model's predicted values are 32.77% of the actual values, suggesting a weak performance of the model in predicting unemployment rate.

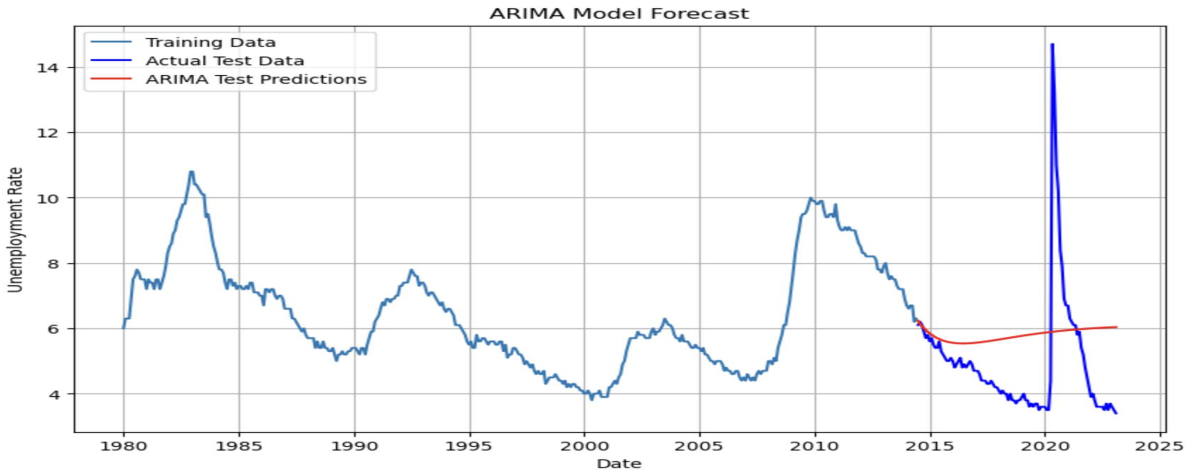

Figure 4: ARIMA Model Forecast

Figure 4 presents the unemployment rate forecast where the red line represents the predicted unemployment rate and the blue line represents the actual unemployment rate. While the initial ARIMA forecast showed a similar downward trend as the actual series but failed in predicting the peak in unemployment caused by COVID-19 pandemic (2020-2021). Although the forecast showed a slight upward trend but seems to be constant afterwards, indicating a weak performance of ARIMA in predicting unemployment rate.

4.2 Experiment 2- LSTM Model

The LSTM model was applied on the unemployment dataset to capture non-linear patterns in which a traditional model like ARIMA might fail. Also, multiple variables like GDP, inflation and change in stock market along with lag features of 6 and 12 months of unemployment rate was included in the model to produce a robust forecast. Additionally, the model's performance was optimized using hyperparameter tuning. Below table contains the performance metrics of LSTM model.

Table 6: Performance metrics of LSTM model

Performance Metrics	Value
MSE	1.5631
MAE	0.4304
MAPE	0.0638

Table 6 indicates that the LSTM model has relatively performed well and showcase a effective performance. The MSE of 1.5631 indicates that the model has managed to minimized large errors. Similarly, a relatively small MAE of approximately 0.43 suggests the average difference between predicted and actual value. Again, the MAPE percentage of 6.38 % reflects a moderate level of accuracy which indicates the model might have faced issues in capturing fluctuations present in unemployment rate.

Figure 5: LSTM Model Forecast

Figure 5 illustrates the LSTM model performance by showcasing the predicted and actual values of unemployment rate over training and testing set. The model was successful in predicting short term trends in the test set as the orange line (actual test data) is closely following the red line (LSTM test predictions) indicating a reasonable accuracy. The LSTM model was also successful in the period of COVID-19 pandemic and has shown upward trend from the year 2020. Finally, the model performance suggests that it has captured complex patterns in the data but with more careful considerations of model tuning and data characteristics the forecast can be improved further.

4.3 Experiment 3- ARIMA-LSTM Hybrid Model

The hybrid model was implemented to capture both linear and non-linear patterns present in the unemployment rate dataset. Initially, standalone ARIMA and LSTM models were applied to capture linear and non-linear components in the data respectively. Following that, both the models predictions were stacked to create a feature set, on which Logistic Regression was later implemented to generate hybrid ARIMA-LSTM model predictions. Using these predictions, the performance metrics below were calculated.

Table 7: Performance metrics of ARIMA-LSTM hybrid model

Performance Metrics	Value
MSE	1.706
MAE	0.466
MAPE	0.0766

MSE value of 1.706 in table 7 indicates that the model was successful in minimizing large errors. The MAE of 0.466 suggests the model was able to predict unemployment rate with some precision. Additionally, the predicted values deviating from the actual values by 7.66 % showcases a moderate performance of the model in terms of predictive accuracy.

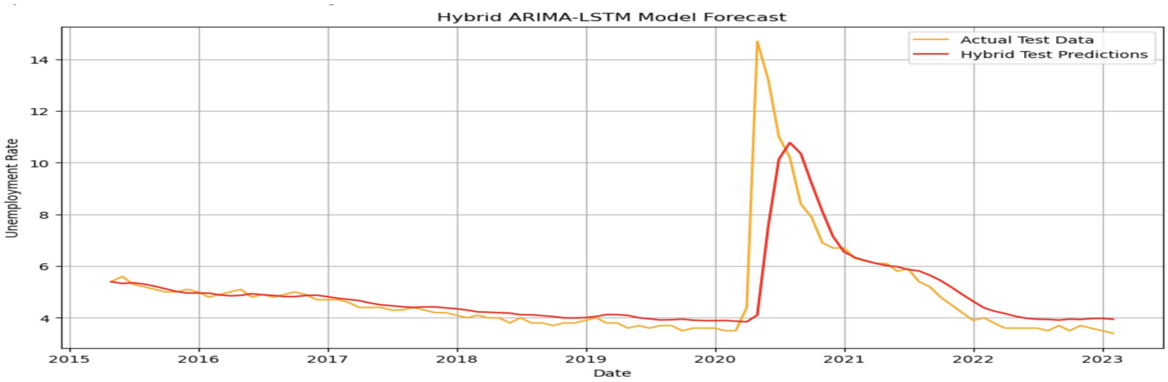

Figure 6: ARIMA-LSTM hybrid model forecast for test values

The hybrid model forecast of figure 6 shows promising results in accurately predicting unemployment rate especially in periods of economic crisis, where the model was able to track the sharp changes in unemployment rate. The red line (Hybrid forecast) was following the yellow line (Actual value) , demonstrating a strong performance by a model on a complex dataset which contains many economic downturns such as the COVID-19 pandemic in 2020.

4.4 Discussion

The LSTM model has outperformed the standalone ARIMA model and has provided competitive results against the ARIMA-LSTM hybrid model. With MSE of 1.5631 and MAE of 0.466, the LSTM has effectively predicted the unemployment rate against the standalone ARIMA and hybrid ARIMA-LSTM model. Both the LSTM and the ARIMA-LSTM hybrid model has showed promising results in predicting peak of COVID-19 pandemic. The better performance of LSTM model can be explained with the use of time step of 10 and optimizing the model through hyperparameter tuning. Also, the inclusion of economic indicators such as GDP, inflation and stock market prices with the lag features of unemployment rate has resulted in better performance of LSTM model. The ARIMA model has failed in predicting unemployment rate, this might be because of its linear nature and the use of a complex dataset which contains multiple economic downturns. Because of the weak performance of ARIMA model, the performance of hybrid model got impacted thus it was not able to produce better results out of all three models.

Table 8: Comparison of ARIMA, LSTM and ARIMA-LSTM models

Model	Strengths	Weakness
ARIMA	• Strong performance in capturing linear patterns • In situations where computational efficiency is required, ARIMA is better than LSTM and ARIMA-LSTM	• Limitations in handling non-linear patterns thus it may struggle during periods of economic crisis. • Relies heavily on historical data, which restricts its ability to predict unforeseen economic downturns. • High error metrics indicates poor performance in predicting economic indicators.
LSTM	• Capable of capturing non-linear and complex patterns in time series data, leading to better performance	• Requires extensive hyperparameter tuning which is computationally expensive and time consuming.

	during economic fluctuations • Utilizes additional economic indicators (GDP, inflation and stock market prices) and lag features for prediction. • Low error metrics indicates strong performance in predicting unemployment rate.	• Sensitive to overfitting, specially with smaller datasets. • Slightly lower performance in predicting certain aspects as suggested by error metrics
ARIMA-LSTM	• Combined the strengths of both ARIMA and LSTM in capturing linear and non-linear patterns. • Balanced approach with moderate error metrics, providing a more comprehensive forecast compared to standalone models. • Performed well during economic downturns, adapting effectively to periods of economic crisis.	• Computationally heavy since it combines two approaches, affecting the model’s ability to perform fast operations. • Extensive hyperparameter tuning required for optimal performance. • Performance is still slightly less accurate than the standalone LSTM model, possibly due to the ARIMA component’s limitations in certain scenarios.

The above comparison table provides a clear view of the strengths and weaknesses of the three models applied, which are ARIMA, LSTM and ARIMA-LSTM. Each model has its own distinctive characteristics that make them suitable for different applications and contexts. ARIMA can be used when computational needs are limited and fast operations are required, whereas LSTM can be used when there are multiple variables involved. However, the hybrid ARIMA-LSTM model, capable of capturing linear and nonlinear patterns, showcased moderate performance against the other two models. Compared to GA-LSTM model of Mero et al. (2024), the ARIMA-LSTM model was outperformed with their MSE of 0.052 [1]. However, the data they used does not contain the economic crisis of COVID-19 and it was applied on Ecuador unlike this research which is based on United States of America.

Regarding the limitations of this study, it is important to point out certain assumptions and constraints that may impact the applicability of the findings to other contexts. First, the research is focused on the data of United States of America and its finding may not be applicable to other regions, since the choice of the model may vary with the region and the characteristics of the unemployment rate [17]. Second, the variables included in this study, which are GDP, inflation and stock market prices, have not impacted as expected and their relations with the unemployment rate can depend on the context and the regions. There may be other demographic factors which might influence the unemployment rate more. Further, the dataset used contained only 518 records, which is relatively small and can be increased further to produce more robust results. Consequently, the generalization of the findings of this study in other contexts should be applied with caution, considering these limitations and the context where the findings are applied.

The selection of the input variable is critical and highly depends on the region and the context [1]. In the USA, there may be other factors that impact unemployment rate more than the selected variables like GDP, inflation and the stock market prices. Though the input variables selected for this study have not shown a high correlation with unemployment rate but including lag features of 6 and 12 months has increased model performance. The LSTM model has shown promising results in predicting unemployment rate, especially during periods of economic crisis.

5 CONCLUSION AND FUTURE WORK

The aim of this research was to accurately predict unemployment rate during sudden economic crisis using a hybrid approach. The research proposes a hybrid approach of a statistical model like ARIMA and a deep learning model like LSTM, to predict the unemployment rate. Other than the hybrid ARIMA-LSTM model, standalone models of ARIMA and LSTM were also employed in this research. This study was carried on the unemployment rate dataset of United States of America, spanning from 1979 to 2023. The performances of these models were evaluated using the performance metrics of MSE, MAE and MAPE. Though the results of standalone LSTM and hybrid ARIMA-LSTM model were comparable, the LSTM model was more efficient during sudden economic changes. The three characteristics influencing unemployment rate; GDP, inflation and stock market prices were used as input for the standalone LSTM model along with lag features (6 and 12 months) of unemployment rate, which enhanced the performance of LSTM model and has resulted in lower error metrics as compared to ARIMA-LSTM and ARIMA. The weak performance of ARIMA model has impacted the hybrid ARIMA-LSTM model predictions in producing slightly less accurate predictions compared to LSTM model. The result of this study indicates that the LSTM model has outperformed the standalone ARIMA and hybrid ARIMA-LSTM model.

The prediction of the unemployment rate is crucial for the economic policymakers, as it enables them to devise effective strategies and policies to regulate labour markets and economic flows within the country. The significance of this research lies in its potential of predicting unemployment rate during economic downturns, which can help prepare the government for future economic challenges. This prior indication will help in formulating monetary policies and strategies aimed for supporting the people.

The analysis of the relation between macroeconomic variables and unemployment rate indicated a weak relationship between them. The selection of influencing variables of unemployment rate is a critical process and totally depends on the context and the region. Furthermore, determining appropriate topology of neural network model like LSTM is very crucial along with optimizing the hyperparameters, since these factors affect a lot on the performance of the model. While using the predictions of this analysis one should remember the context and the region of dataset along with highlighted limitations of this research in discussion section.

This work can be improved by implementing the hybrid ARIMA-LSTM and standalone LSTM model on the unemployment dataset of different countries to test its performance. Additionally, other macroeconomic variables can be explored like minimum wage, producer price index, exchange rates, energy consumption and other demographic factors. Also, the performance of the ARIMA model can be improved by using exogenous variables, which will help the model in predicting for periods of economic downturns. Other possible extensions include the application of other hybrid models like ARIMA-ARNN, ARIMA-ANN, ARIMA-GRU and ARMAX-GARCHX for predicting unemployment rate. These model's performances can be compared with the ARIMA-LSTM and standalone LSTM model so that a robust approach can be devised to predict unemployment rate, which will help formulate effective strategies to counter economic challenges.

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