**First Research paper’s findings**

As with any economic forecasting endeavor, predicting unemployment in the European Union necessitates carefully selecting and using appropriate methodology. The potential of machine learning approaches has been highlighted by numerous studies that have examined a variety of forecasting models, both conventional and new.

In one such study, which compared machine learning with conventional time series models for forecasting inflation, it was discovered that the "best" model depended on the particular economic indicator being anticipated as well as the prediction horizon. The authors made an argument for the need for flexible model selection in forecasting, which is a realization that applies to forecasting unemployment.

In addition, the study indicated that machine learning models fared well with erratic and volatile series (Ülke, Sahin & Subasi, 2018). In the field of economic forecasting, where unforeseen events and uncertainties are widespread, this trait is very helpful. This shows how machine learning models have the ability to manage the volatility and inconsistencies in unemployment data.

The study also emphasized the significance of taking multivariate models into account. These models frequently outperformed their univariate counterparts since they account for a variety of interrelated variables (Ülke, Sahin & Subasi, 2018). Multivariate models might offer a more thorough examination because several economic, social, and political variables have an impact on unemployment rates.

The Root Mean Squared Error (RMSE) and R-squared (R2) metrics, both of which are common in the field of forecasting, were employed to assess the effectiveness of the forecasting models (source). The precision of predictions and the model fit to the data can both be evaluated using these metrics.

Significantly, the study discovered that the best model differed depending on the length of the projection, suggesting that various models may be more appropriate for forecasting over the short term as opposed to the long term. This finding implies that while choosing a model for unemployment forecasting, it is important to carefully evaluate the target prediction horizon. In conclusion, the research underlines the value of selecting a model that is specifically suited to the characteristics of the data and the forecasting objectives while also demonstrating the potential of machine learning and multivariate time series models for unemployment forecasting. This understanding informs how we forecast unemployment in the European Union, allowing us to choose and use models in a flexible, data-driven manner.

Ülke, V., Sahin, A. and Subasi, A., 2018. A comparison of time series and machine learning models for inflation forecasting: empirical evidence from the USA. Neural Computing & Applications, 30(5), pp.1519-1527. DOI:10.1007/s00521-016-2766-x.

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| Author | Dataset | Problem description | Research question | methodology | limitation |
| Ülke, V., Sahin, A. and Subasi(2018) | Forecasting inflation in the USA | compares the effectiveness of time series and machine learning models in forecasting inflation in the US | 1. Predicting unemployment rates and inflation rates in the USA  2. Comparing time series models with machine learning  3. Finding how forecasting accuracy varies with time like 1st quarter, 2nd quarter, and 3rd quarter | 1.Autoregressive model and Naïve model  2. Autoregressive distributed lag model  3. Vector autoregressive regression model  4. k-Nearest neighbor model  5. Artificial neural network model  6. Support vector regression model | 1. The conclusions may be less applicable to other regions with distinct economic structures and market dynamics because they mostly use data from the USA. |
| Karim, Pardede, and Mann(2023) | Time Series Forecasting Incorporating Google Trends Data in Australian Macro Indicators | Finding the best model to correctly forecast Australian economic indicators while taking unforeseen global events into account is the issue. | 1. Can data from Google Trends improve the predictability of Australian economic indicators?  2. Which forecasting model delivers the best results for the chosen economic indicators?  3. Does the incorporation of COVID-19 data alter the precision of the forecasting models?  4. How do classical models (like SARIMA) perform in comparison to deep learning and machine learning models (like SVR and CNN)? | 1. SARIMA  2. Support vector regression model  3. CNN | 1. Due to cultural, economic, and geographic differences, the study is only applicable to Australia; hence, the conclusions may not extend to other nations.  2. The study mainly relies on Google Trends data, which is susceptible to changes in Google's methods for gathering and using user data.  3. The results of the forecasting were found to vary on the precise method employed and the forecasting horizon, suggesting that the models might not be appropriate in all situations. |
| Mutascu, M.  and Hegerty, S.W( 2023) | Predicting the contribution of artificial intelligence to unemployment rates: An artificial neural network approach. | Forecasting unemployment is necessary, especially given the rapid advancements in AI and their potential effects on labour markets. | Can developed, high-tech economies predict unemployment using an ANN model?  What role does artificial intelligence, as represented by AI patents, play in predicting unemployment?  How do additional factors like total population, labour productivity, and lagged unemployment affect the model? What about foreign direct investment? | Artificial Neural Network (ANN)  ARIMA  SARIMA | 1. The research is limited to high-tech, industrialized economies, and therefore might not generalize well to emerging ones.  2. Using an ANN with only one layer and 10 neurons could oversimplify relationships.  3. The data only goes up to 2016. |
| Yurtsever, M. (2023) | Advancing Unemployment Forecasting in the EU through a Hybrid LSTM-GRU Model | The importance of unemployment rates as indicators of the state of the economy and society has an effect on investments and policy. The ability to predict these rates accurately is essential for efficient planning and decision-making. | 1. Can the forecast of the unemployment rate be made more accurately using a hybrid LSTM-GRU model?  2. When compared to solo LSTM and GRU models, how effective is the hybrid model?  3. What are the advantages and disadvantages of the suggested hybrid strategy? | Long Short-Term Memory (LSTM)  Gated Recurrent Unit(GRU)  Evaluation metrics such as MAE, RMSE and MAPE | 1.Results could be influenced by unaccounted-for exogenous factors like economic condition.  2There are no performance significance tests.  3. Hyperparameter tuning's effects are not explored.  4.Not clearly addressed are study limitations and predictive uncertainty. |

Research questions that could be addressed in my research were.

1. When predicting unemployment rates in the EU, how do conventional time series models and machine learning models compare?
2. Which models offer the best precise predictions for various unemployment indices among EU member states?
3. How do these models' results differ between EU members in terms of performance?
4. How does forecast accuracy change across various time frames (quarterly, monthly, and annually)?
5. How well do these models perform in a specific year () of simulated out-of-sample forecasting?
6. Can more volatile and erratic series in unemployment data be forecasted more accurately using machine learning models?
7. How resistant are these prediction models to rapid economic shocks, such as recessions or the COVID-19 epidemic?

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<https://link.springer.com/article/10.1007/s10614-019-09908-9>

Suggested Titles for research

* Machine Learning vs. Traditional Time Series Approach for Predicting EU Unemployment Trends
* An assessment of unemployment rate forecasting models among EU member states
* Using Predictive Analytics: A Deep Dive into European Union Unemployment Forecasting
* A Machine Learning Approach vs. a Traditional Time Series Approach for Accurate Unemployment Forecasting in the EU

# Second Research Paper Findings(A Model Selection Approach for Time Series Forecasting: Incorporating Google Trends Data in Australian Macro Indicators)

It's crucial to take into account how cutting-edge data sources and data analytics techniques can improve our prediction powers when creating an efficient and trustworthy unemployment forecasting model for the European Union. Existing research offers helpful insights in this area, such as the study carried out by Karim, Pardede, and Mann (2023) in Australia.

Another crucial component of macroeconomic forecasting is the choice of suitable forecasting models. Karim, Pardede, and Mann (2023) used a combination of deep learning (CNN), machine learning (SVR), and classical time series linear regression (SARIMA). The effective application of a mixed-model method in this study provides a strong justification for using a similar technique in this project, where time series and machine learning models will be combined for EU unemployment forecasting.

This study should take into account the Australian study's (Karim, Pardede, and Mann, 2023) observation that predicted accuracy depends on the forecasting horizon. It emphasizes how crucial it is to pick a forecasting model that is compatible with the time horizon for which we intend to anticipate unemployment rates in the EU.

Additionally, Karim, Pardede, and Mann (2023) suggested a data-driven approach for picking the top-performing model out of a variety of options. This strategy is an excellent example of optimal practice in model selection and a helpful point of reference for this study. It encourages us to use a similar approach, improving the accuracy of our model selection procedure.

Last but not least, the Australian study (Karim, Pardede, and Mann, 2023) emphasized the value of feature selection for accurate prediction. This realization emphasizes the importance of careful feature selection in this study and highlights the requirement to find and include the best predictive variables in our models.

Given the foregoing debate, this study will expand upon the insightful approaches and information acquired from earlier research, such as that of Karim, Pardede, and Mann (2023), while specifically applying them to the field of EU unemployment forecasting.

**Reference**

Karim, A.A., Pardede, E. & Mann, S., 2023. A Model Selection Approach for Time Series Forecasting: Incorporating Google Trends Data in Australian Macro Indicators. Entropy, 25(8), p.1144. Available at: http://dx.doi.org/10.3390/e25081144 [Accessed 1 August 2023].

**THIRD Paper Research Findings**  
Understanding the effects of artificial intelligence on global employment patterns has become crucial, especially in industrialized nations with a high level of technological development. This study aimed to forecast unemployment rates in 23 such economies over the period of 1998 to 2016. It included conventional models like ARIMA and SARIMA as well as Artificial Neural Networks (ANN), so it didn't solely rely on contemporary forecasting techniques.

With a high coefficient of determination of 0.912, the ANN model, particularly when created with a single layer and 10 neurons, demonstrated excellent skill in forecasting. Artificial intelligence, as measured by the number of related patents, became a significant factor in the forecasting process. It's crucial to remember, though, that while AI stood out in the predictions, it wasn't pinpointed as a direct contributor to unemployment. Instead, it stands for prospective difficulties in the labour market brought on by automation and innovation. When considering socioeconomic issues in further detail, Foreign Direct Investment (FDI), demographic trends, labour productivity, and historical unemployment statistics all showed a strong impact on the forecast. However, factors like inflation and the size of the government played much smaller roles.

The research has limits, despite the encouraging findings acquired. The study's overall application might be limited if it just looks at high-tech, wealthy countries. Furthermore, the data only goes back to 2016, ignoring recent trends and events that may have had a profound impact. Additionally, it is often difficult to distinguish between correlation and causation, which is particularly clear when analysing how FDI protects against unemployment.

In essence, the study emphasizes the significance of a comprehensive forecasting strategy that integrates both cutting-edge AI-driven technologies and tried-and-true models. It is a call to action for decision-makers and other interested parties to establish policies that are both proactive and reactive, taking into account the many different factors that may shape future labour markets in developed regions.

Mutascu, M. and Hegerty, S.W., 2023. Predicting the contribution of artificial intelligence to unemployment rates: an artificial neural network approach. Journal of Economics & Finance, 47(2), pp.400-416.

**Fourth Research Paper findings:**

This work takes a risk by providing a cutting-edge hybrid strategy that combines the strength of Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) approaches in the dynamic field of economic forecasting. The need to improve the accuracy and dependability of estimates of the unemployment rate inside the European Union (EU) is what motivates the research. The suggested hybrid model appears as a viable tool for improving the accuracy of unemployment estimates by smoothly incorporating deep learning techniques and utilizing historical data patterns.

The research orchestrates a thorough evaluation of the performance of the hybrid model using a large dataset that includes four key EU countries: the US, UK, France, and Italy. Comprehensive comparisons with conventional standalone LSTM and GRU models are part of the holistic approach. It is encouraging to note that the hybrid model constantly takes the lead, demonstrating stronger forecasting ability in a range of economic scenarios.

This study captures the critical intersection of economic analysis and technical innovation. The hybrid approach offers policymakers, analysts, and stakeholders a game-changing opportunity by combining the power of machine learning and time series analysis. The study not only offers a practical solution to the urgent problem of predicting unemployment, but it also sheds insight on the paradigm change happening in economic analytics.

Despite the excitement, the study is still aware of its own inherent limits, which call for cautious evaluation. The accuracy and representativeness of the underlying data are crucial to the hybrid model's effectiveness. Furthermore, the complex interactions between external causes and economic conditions add a level of unpredictability that must be acknowledged. Statistical significance tests to confirm observed performance differences are noticeably absent, which is a point that potential future research might touch on. Furthermore, the possible impact of hyperparameter adjustment on model correctness highlights the necessity of thorough model optimization techniques.

This research imagines a time where advanced algorithms and careful data analysis work together to improve economic forecasts. The work advances economic forecasting methodologies by outlining a novel hybrid model and openly acknowledging its drawbacks. This program not only demonstrates the development of data-driven decision-making, but it also serves as a catalyst for wise policy decisions that influence the EU's economic environment.

Yurtsever, M. (2023) ‘Unemployment rate forecasting: LSTM-GRU hybrid approach’, Journal for Labour Market Research, 57(1), pp. 1–9. doi:10.1186/s12651-023-00345-8.