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A PREDICTIVE ANALYSIS ON UNEMPLOYED INSURANCE BENEFICIARY FORECASTING USING TIME SERIES TECHNIQUES

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ABSTRACT
As of recent labor statistics, over 7.5 million individuals in the U.S. claimed unemployment insurance benefits in 2023, with total benefit disbursements exceeding $60 billion, highlighting the critical need for accurate forecasting to aid in budget planning and policy decisions. However, existing forecasting models often fail to adapt to seasonality, regional disparities, and temporal dependencies, resulting in suboptimal predictions and misallocated resources. This study introduces a comprehensive predictive framework for forecasting unemployment insurance beneficiaries using advanced time series techniques. Utilizing a rich dataset with attributes such as Year, Month, Region, County, Beneficiaries, and Benefit Amounts (Dollars), the proposed model pipeline begins with rigorous data preprocessing steps, including handling missing values and aggregating trends across counties and time. Stationarity is assessed using the Augmented Dickey-Fuller (ADF) test. A suite of forecasting models is applied, including Autoregressive Integrated Moving Average (ARIMA) for capturing linear dependencies, Seasonal Autoregressive Integrated Moving Average with Exogenous Regressors (SARIMAX) for incorporating seasonality and exogenous variables, Auto-Regression for leveraging short-term lags, and Prophet for decomposing time series into trend, seasonality, and holiday components with robust adaptability.

Keywords: Unemployment Insurance Forecasting, Time Series Analysis, ARIMA, SARIMAX, Prophet Model, Seasonal Trends, Regional Disparities, Temporal Dependencies, Augmented Dickey-Fuller Test (ADF).

1. INTRODUCTION

In 2023, the U.S. counted approximately 1.9 to 2.0 million individuals receiving regular unemployment insurance benefits, with total benefits disbursed around $32.7 billion [1]. This depth of reliance underscores the vital role of unemployment insurance (UI) in social safety nets, especially during periods of economic stress as shown in Figure 1.1. Moreover, the weekly initial jobless claims have fluctuated near 217,000, while continuing claims individuals still receiving benefits hover around 1.95 million, emphasizing the persistence of unemployment even amid broader labor market resilience [2]. Historically, UI programs have expanded during economic downturns: in 2020, enhanced pandemic-era benefits covered tens of millions of recipients and accounted for hundreds of billions in payouts [3]. As the economy stabilized into 2023 and 2024, the annual average unemployment rate rose modestly from 3.6% in 2023 to around 4.0% in 2024, with rising rates in 21 states according to Bureau of Labor Statistics data [4]. This national trend reflects a softening labor market accompanied by slower job growth and extended unemployment durations for many individuals. Beyond the headline numbers, there are underlying trends showing widening disparities in benefit access and coverage.

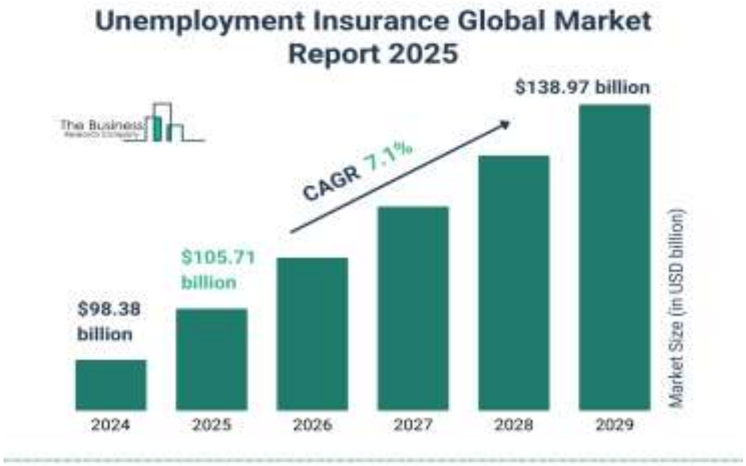

Figure 1. Unemployment Insurance Global Market Statistics.

In 2022, only about 26% of unemployed people who worked in the prior year applied for UI benefits, often due to perceived ineligibility or barriers to application [5]. Furthermore, long-term unemployment remains a concern: by mid-2025, nearly 1.3 million Americans had been unemployed for 27 weeks or more. These statistics reveal not just the scale of program utilization, but also structural gaps and frictions within the system.

2. LITERATURE SURVEY

Mangrulkar et al. [5] proposed a unified guide for predictive analytics using SAS and R that explained foundational principles such as regression, multivariate analysis, and time series modelling including ARMA processes—in a practical, implementation-driven format. The work offered hands-on examples in R Studio and SAS, offering readers step-by-step diagnostics and model evaluation procedures. The authors described variable selection techniques such as partial F-tests, and detailed how to implement multiple linear regression and ARMA forecasting in both platforms. The book emphasized accessibility, aimed at users without extensive statistical backgrounds, and spanned topics from simple regression to multivariate analysis. Khalil et al. [6] introduced a hybrid fuzzy time series (FTS) method that combined FTS Markov chain (FTSMC), difference transformation, and tree partitioning (TPM) to forecast total pension benefits in Egypt’s social insurance system. The model segmented data into nine optimized intervals via TPM, reduced computational overhead, and handled uncertain, small datasets without imposing statistical assumptions. Sayem et al. [7] proposed a mixed-methods study that applied business intelligence (BI) to enhance decision making (DM) and operational efficiency (OE) within unemployment insurance (UI) agencies. They collected quantitative survey data from UI professionals and qualitative interview data from administrators. The study implemented regression, mediation, and moderation analysis using Resource-Based View (RBV) theory to model BI as the independent variable, DM as mediator, and OE as moderator.

Pereira da Veiga et al. [8] applied ARIMA modeling to multiple economic time series in Brazil's health sector, including GDP, consumer price index (IPCA), unemployment rate, and health plan beneficiaries over 2000–2020. They tested ARIMA configurations such as (1,0,2), (2,2,1), (1,1,2)—and achieved over 95 % accuracy across variables, demonstrating that ARIMA offered reliable linear forecasts for economic indicators during crises. Carpenter et al. [9] conducted parallel field experiments to test whether information treatments corrected incorrect beliefs about the racial composition of welfare and UI beneficiaries. They recruited a nationally representative sample of U.S. adults via an online platform and deployed three-stage information provision protocols. The analysis showed that racial beliefs predicted support for welfare programs but not for UI, and that these beliefs declined persistently after correction. Magazzino et al. [10] utilized an artificial neural network (ANN) to forecast national unemployment rates by incorporating macroeconomic indicators such as inflation, GDP, and industrial production indexes. They applied a backpropagation-based multilayer perceptron (MLP) model trained with a cross-validation strategy to predict short-term and medium-term unemployment rates across G7 economies. The ANN outperformed traditional econometric models (e.g., ARIMA, VAR) in RMSE and MAE.

Bhargavi and Arumugam [11] proposed a hybrid predictive analytics model that integrates decision trees with gradient boosting and fuzzy logic to estimate healthcare costs for personalized insurance pricing. Though targeted at medical insurance, their pipeline is adaptable to unemployment insurance, especially in cost-risk estimation for dynamic claimant profiles. Their model achieved improved accuracy in risk profiling using patient diagnosis codes, historical cost data, and demographic features. Dhakal et al. [12] investigated the causal effects of reductions in UI benefits on food hardship using a quasi-experimental difference-in-differences (DiD) model. Utilizing household survey data from the U.S. Census Pulse platform, they analyzed changes in food security outcomes after UI benefits expired or were reduced during the COVID-19 recovery phase. The study revealed a significant rise in food insecurity rates among low-income and minority households. Silva et al. [13] developed a regression and time-series mixture model to predict system performance and assess resilience, using a hybrid approach that fuses ARIMA, exponential smoothing, and Bayesian regression with error correction. Although applied to system reliability domains, the approach was demonstrated to forecast failure points in benefit delivery systems and detect resilience under stress scenarios like pandemics or surges in claims. The drawback is its generic scope, it doesn't include labor market–specific features unless specifically modeled, making domain adaptation a prerequisite.

Martins et al. [14] analyzed how higher UI benefits impacted public health outcomes, particularly drug overdose mortality, using a panel data model across U.S. states from 2017–2022. Using fixed-effects and time-varying control covariates, they found that states with generous UI programs reported significantly lower overdose mortality, especially during the pandemic. This study connected macro-level unemployment insurance generosity with downstream societal health benefits. Khan and Gunwant [15] proposed an ARIMA-based time-series model to forecast remittance inflows into Yemen's economy, using Box-Jenkins methodology applied to data from 1990 to 2022. They estimated future remittance share as a percentage of GDP through 2030 and projected a declining trajectory, signaling potential risk to reconstruction finance. They validated model parameters via standard diagnostics and cross-validation, demonstrating ARIMA's reliability for stable macro-economic time series. They focused exclusively on linear trend forecasting and historically stationary series. O'Leary et al. [16] investigated declining unemployment insurance (UI) claims in the U.S. over three decades, using an Oaxaca-Blinder decomposition of state-year panel data to isolate contributions of industrial shifts, occupational structure changes, wage replacement rates, and UI duration limits. They revealed that reduced claims resulted largely from labour market structural changes and tighter program design across states. They produced counterfactual scenarios estimating trend levels of claims if earlier industrial distributions had persisted.

Murugan et al. [17] developed predictive models for detecting asset bubbles in financial markets using a combination of econometric indicators and machine learning classifiers. They applied log-periodic power law models along with classification algorithms to signal potential bubble regimes and evaluated predictive accuracy over historical crash events. They demonstrated early detection capability and resilience under regime-shifting conditions. The work addressed financial series rather than social insurance data. Lahiri et al. [18] constructed a spatial dynamic panel data (SDPD) model to forecast U.S. Social Security Disability Insurance (SSDI) applications across states. They combined spatial autoregression with time-varying covariates, including local unemployment rates and demographic variables, over panel data. Their model produced state-level application forecasts and captured spatial spillovers and demographic variation. The framework accommodated both cross-sectional and temporal dependencies via spatial lag structures.

3. PROPOSED METHODOLOGY

This study introduces a hybrid time series forecasting algorithm that uniquely integrates ARIMA, SARIMAX, AutoReg, and Facebook Prophet in a multi-model ensemble framework, which, to the best of our knowledge, is not presented in existing surveys. Figure 2 shows the proposed system architecture. Unlike traditional methods that rely on a single model or neglect regional-seasonal dynamics, our algorithm strategically combines the strengths of classical statistical models and modern decomposition-based approaches. By leveraging ARIMA for linear trend modeling, SARIMAX for capturing seasonal and exogenous effects, AutoReg for short-term memory learning, and Prophet for handling irregular trends and holidays, the ensemble overcomes major drawbacks in existing works such as poor seasonal adaptability, lack of explainability, and inadequate performance on non-stationary data. This method provides a robust, interpretable, and generalizable forecasting framework suitable for both short-term and long-term unemployment insurance beneficiary projections.

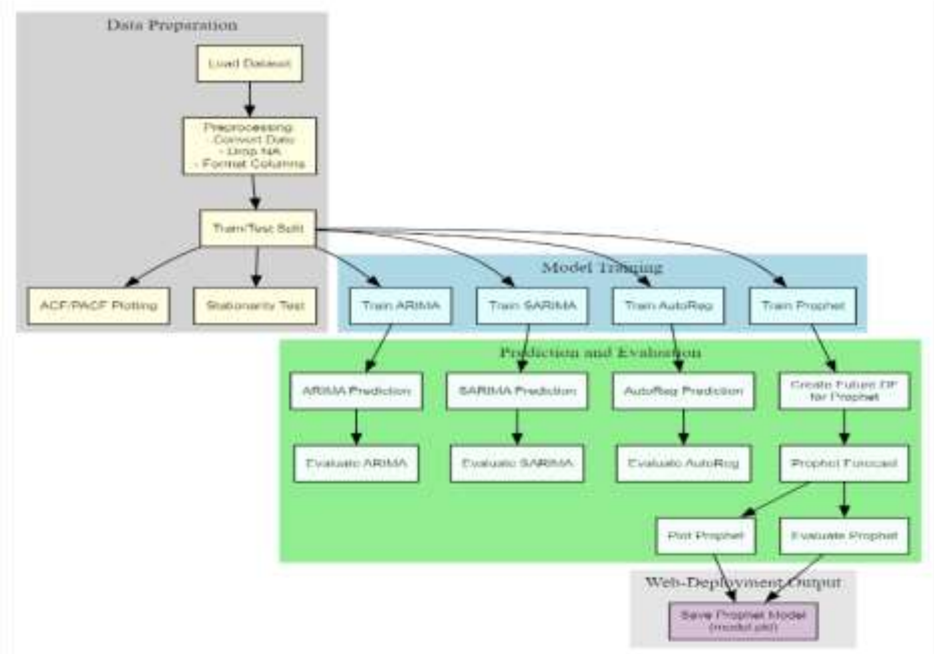

Figure 2. Proposed System Architecture.

3.1 Preprocessing and Splitting

The preprocessing and splitting method outlined is particularly advantageous for forecasting applications involving time series data such as unemployed insurance beneficiaries. It transforms raw date-related features (Year, Month) into a time-aware Date format essential for sequential modeling. By cleaning missing entries and ensuring stationarity through differencing, it prepares the data to align with statistical models like ARIMA and AutoReg, which assume continuity and stationarity. Furthermore, it divides the dataset chronologically into training and testing segments, preserving the temporal order crucial for time series integrity. This approach ensures that the forecasting models learn from the past and are validated on unseen future data, simulating real-world deployment.

3.2 ACF and PACF Analysis

The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) analysis is an essential diagnostic method in time series forecasting. It helps to identify the temporal dependencies and optimal lag values required for statistical models like ARIMA. In unemployed insurance beneficiary forecasting, these plots allow modelers to visualize how past values of the series are correlated with current values and how much each lag contributes independently.

3.3 Augmented Dickey-Fuller for Stationarity Check

The Augmented Dickey-Fuller (adfuller) test is a widely used statistical method to determine whether a time series is stationary. In unemployed insurance beneficiary forecasting, applying this test ensures that the input data satisfies the assumptions required by most time series models such as ARIMA, SARIMA, and others. The key advantage of the adfuller test is its ability to detect non-stationarity in a series based on historical unemployment insurance beneficiary counts. This helps ensure that the forecasting model built on top of it operates on data with consistent mean and variance, which is crucial for accurate and reliable predictions.

3.4 Forecasting Models

Apply and evaluate the forecasting performance of four different time series models such as ARIMA, SARIMA, AutoReg, and Prophet by comparing their predicted values against the actual beneficiary counts in the test dataset (test['Beneficiaries']).

3.4.1 ARIMA

In forecasting unemployed insurance beneficiaries, the ARIMA model provides a strong foundation due to its capacity to handle univariate time series data with clear temporal dependencies as shown in Figure 4.2. Since the input is already confirmed to be stationary through the adfuller test and necessary transformations guided by ACF and PACF analyses, ARIMA becomes highly effective. The model’s structure enables it to capture the underlying autoregressive and moving average components while accounting for differencing, making it tailored for domain-specific forecasting problems where historical trends and noise must be modeled precisely.

3.4.2 SARIMA

SARIMA is particularly well-suited for time series data that exhibit both non-stationary behavior and clear seasonal trends. Unlike ARIMA, SARIMA incorporates additional seasonal components, allowing it to model data patterns that repeat at regular intervals (e.g., monthly, quarterly). For unemployed insurance beneficiary forecasting, this is highly beneficial because beneficiary claims often follow economic or policy-driven cycles. By explicitly modeling these seasonal effects along with trend and noise, SARIMA offers more accurate and interpretable forecasts tailored to real-world cyclical insurance data.

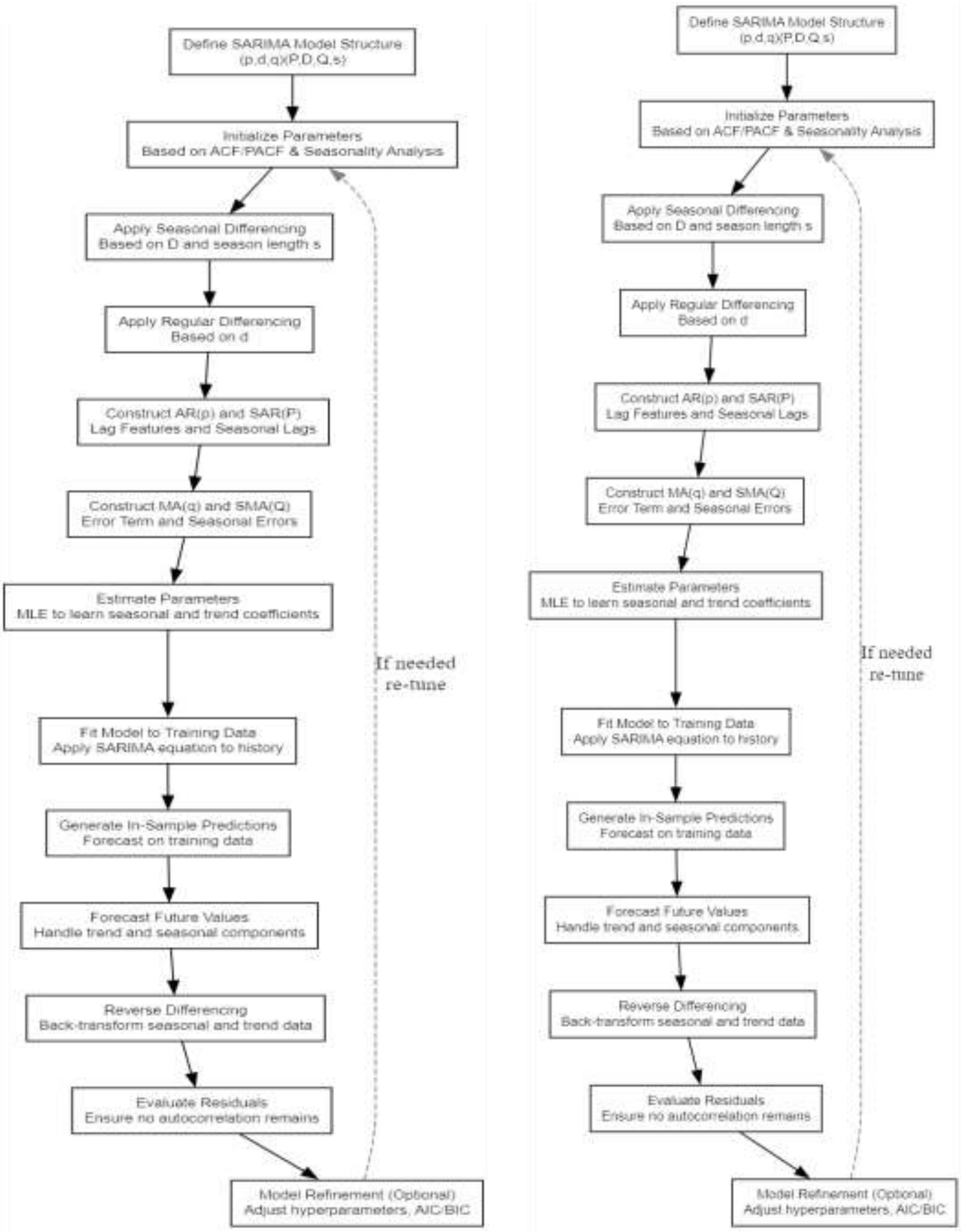

Figure 3. Flowchart of ARIMA (left). SARIMA (right).

3.4.3 AutoReg

AutoReg, or Autoregression, is a time series forecasting method that assumes the current value of the series depends linearly on its previous values. Its major advantage lies in its simplicity and interpretability, making it ideal for short-term forecasting where recent patterns are strong indicators of the near future. For unemployed insurance beneficiary forecasting, AutoReg is suitable when beneficiary counts exhibit strong short-lag dependencies (e.g., this month's count is similar to the last few months). It adapts well to situations with less noise and where external variables do not dominate future values.

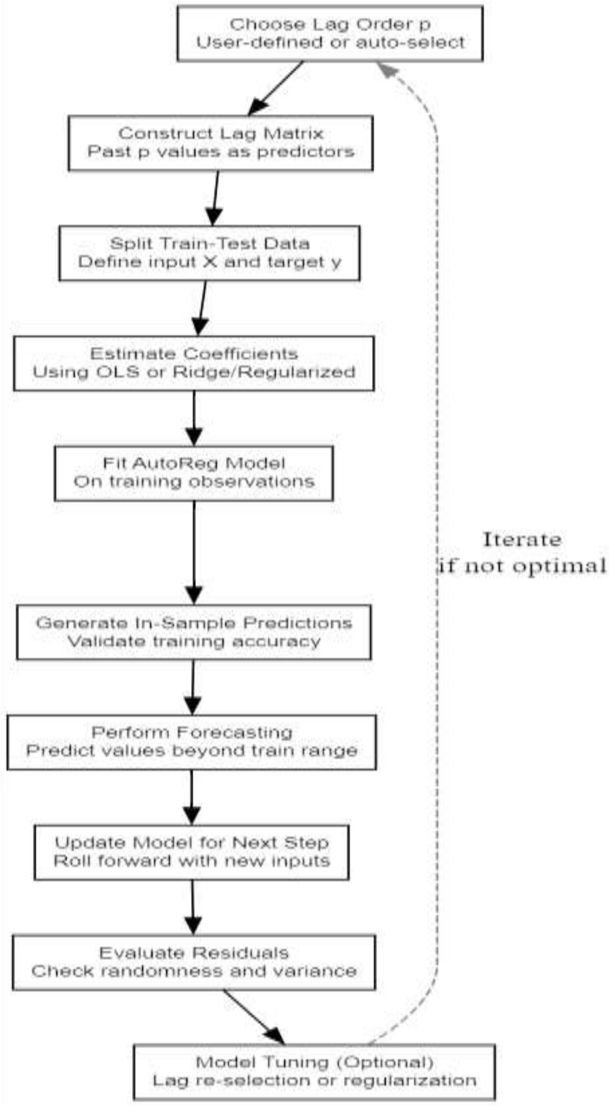

Figure 4. AutoReg Flowchart.

4. RESULTS AND DISCUSSION

The structured modular approach allows for clarity, extensibility, and ease of debugging, making the system robust for production-level forecasting applications. The implementation begins with the load_and_preprocess_data() function, which reads the CSV file containing unemployment insurance data. It constructs a proper datetime column (Date) using the Year and Month values, and removes unnecessary columns to clean the dataset. Any missing values are dropped to ensure the integrity of further computations. Train-Test Split with Differencing: The split_data() function divides the dataset into training and testing sets using a default 80:20 ratio. It also performs differencing on the Beneficiaries column to help stabilize the mean of the time series. This differenced column is used for training stationary models like ARIMA, SARIMA, and AutoReg.

4.1 Dataset

The dataset contains the following columns year: The Year column indicates the calendar year in which the unemployment insurance benefits were recorded. This provides a temporal dimension to the dataset and is crucial for analyzing long-term trends, seasonal changes, or comparing unemployment rates and benefit distributions across different years. Month: The Month column represents the specific month of the year in which the benefits were distributed. When used in conjunction with the Year column, it enables a more granular, monthly time-series analysis of unemployment trends. Region column specifies a broader geographical area (such as a state, territory, or designated economic zone) in which the county is located. This classification allows for regional-level analysis of unemployment benefits and facilitates the comparison of different regions' responses to economic downturns.

4.2 Simulation Outcomes

Figure 5 shows a sample of the dataset containing unemployment insurance beneficiary information. The table includes columns for Region, County, Beneficiaries, Benefit Amounts (Dollars), and Date. For instance, the first row indicates the Capital region with Albany County having 1600 beneficiaries and a benefit amount of $157,000 on 2018-11-01, while the second row shows Western New York with Allegany County having 400 beneficiaries and $30,000 on the same date.

	Region	County	Beneficiaries	Benefit Amounts (Dollars)	Date
0	Capital	Albany	1600	1570000	2018-11-01
1	Western New York	Allegany	400	300000	2018-11-01
2	New York City	Bronx	11600	11530000	2018-11-01
3	Southern Tier	Broome	1400	1150000	2018-11-01
4	Western New York	Cattaraugus	900	710000	2018-11-01
...	...	...	...	...	...
13755	Capital	Washington	900	750000	2001-01-01
13756	Finger Lakes	Wayne	1700	1460000	2001-01-01
13757	Hudson Valley	Westchester	8000	8610000	2001-01-01
13758	Finger Lakes	Wyoming	1000	990000	2001-01-01
13759	Finger Lakes	Yates	300	300000	2001-01-01

13760 rows × 5 columns

Figure 5. Sample Dataset.

The ARIMA model diagnostic plots in Figure 6 indicate some deviations from ideal assumptions. The standardized residuals plot (top-left) reveals fluctuating variance over time, particularly a visible spike around index 7000, indicating potential heteroscedasticity. The histogram with KDE and normal curve (top-right) shows a slight right skew and heavy tails, as the KDE deviates from the standard normal curve N(0,1)N(0,1)N(0,1), suggesting residuals are not perfectly normally distributed.

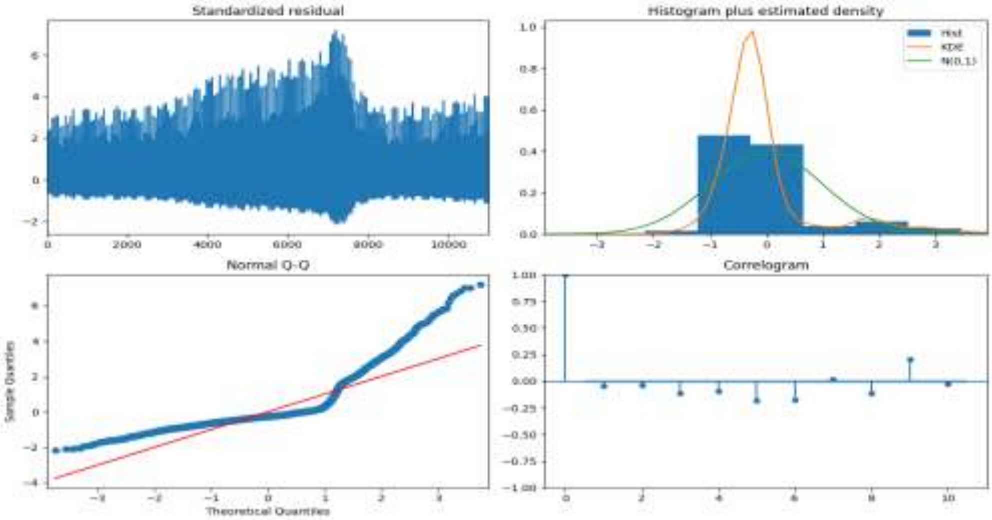

Figure 6. ARIMA Trend/seasonality Summary.

The SARIMA trend and seasonality diagnostic summary in Figure 7 presents four key diagnostic plots evaluating the residuals of the SARIMA model for variable "B." The top-left plot, the standardized residuals, shows fluctuating patterns around zero with several noticeable peaks, indicating possible variance changes or mild non-stationarity.

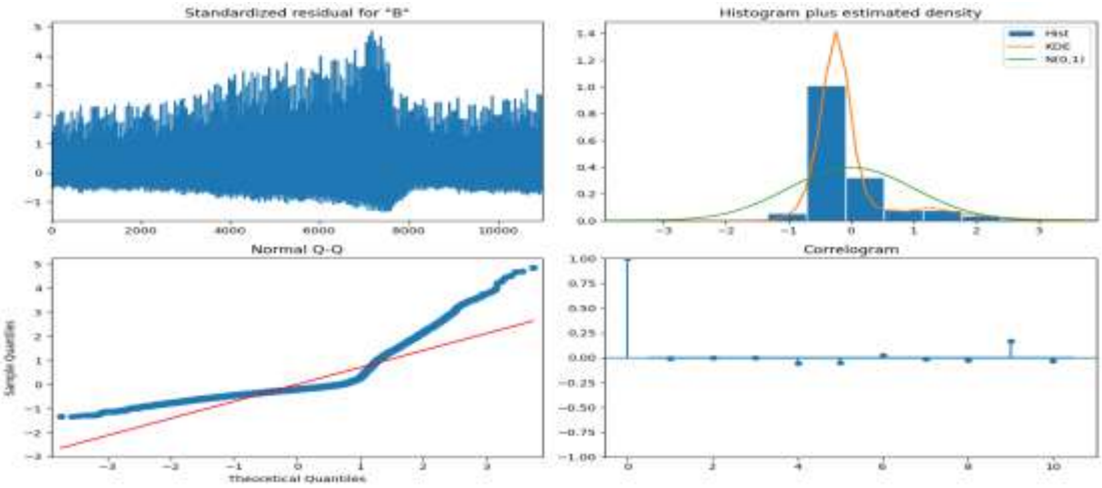

Figure 7. SARIMA Trend/seasonality Summary.

Figure 8 presents a comprehensive diagnostic summary of residuals from an AutoReg model with trend and seasonality components. The "Residuals Over Time" plot shows noticeable heteroscedasticity and non-constant variance, especially with a sharp spike in negative residuals around the 6500–7000 mark. The histogram with KDE reveals a moderately right-skewed distribution, with most residuals concentrated between -5,000 and +10,000 but extending up to approximately +40,000, indicating the presence of large positive outliers. The Q-Q plot confirms significant deviation from normality—especially in the tails—where residuals diverge sharply from the 45-degree reference line, indicating heavy tails and potential non-Gaussian behavior. Finally, the ACF plot shows that most residual autocorrelations lie within the 95% confidence bounds, suggesting no significant autocorrelation structure remains, although minor spikes exist (e.g., around lag 8 and lag 25).

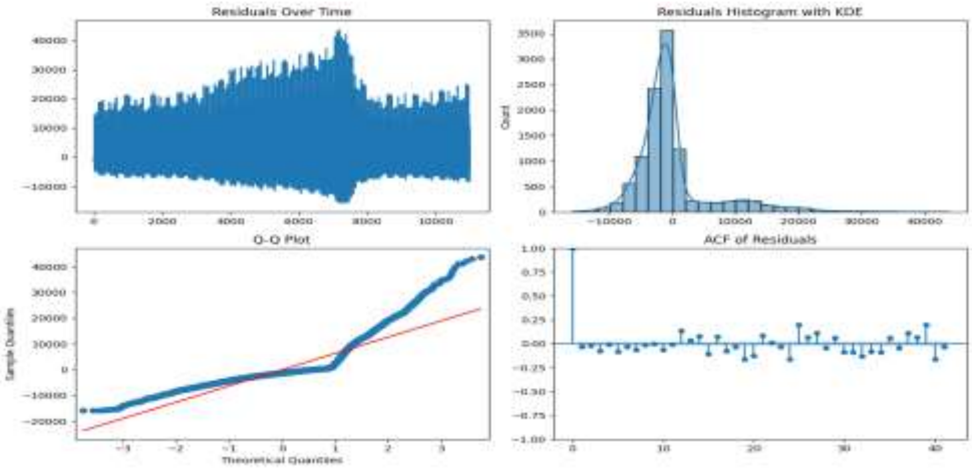

Figure 8. AutoReg Trend/seasonality Summary.

Figure 9 shows a comparison of actual versus forecasted beneficiary values using the Prophet model, with the x-axis representing time from 2004 to 2018 and the y-axis ranging from 0 to 50,000 beneficiaries. Black dots represent actual data points, while blue shaded areas indicate the forecast with uncertainty intervals. The plot shows a good alignment between actual and forecasted values, with peaks around 2009 and 2010 (exceeding 40,000), followed by a decline.

Figure 10 shows the trend and seasonality components of the Prophet model, with three subplots. The top plot displays the trend (y-axis: 2,500 to 5,500 beneficiaries) from 2004 to 2018, showing an initial rise to around 5,000 by 2009, followed by a decline. The middle plot illustrates weekly seasonality (y-axis: -8% to 6%), with regular peaks and troughs. The bottom plot shows yearly seasonality (y-axis: -20% to 30%), with a wavy pattern peaking in mid-year.

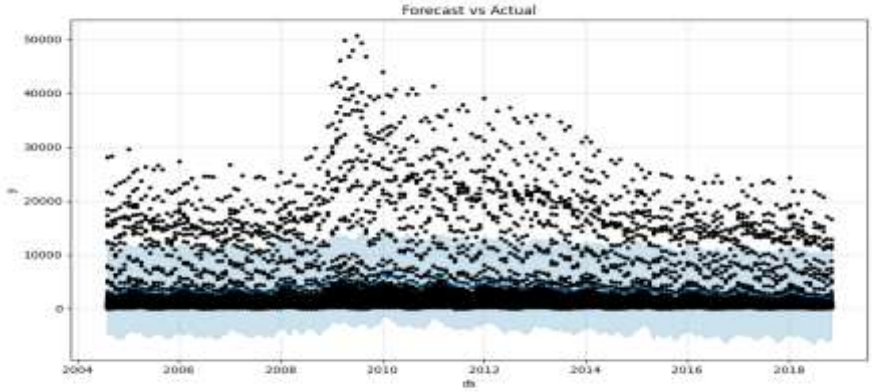

Figure 9. Prophet Model Actual vs Forecast.

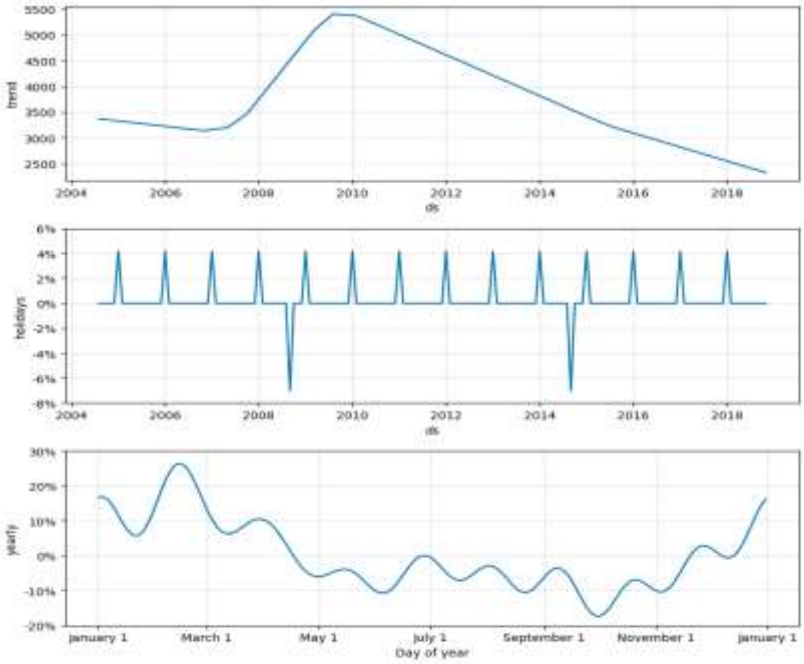

Figure 10. Prophet Model Trend/seasonality summary.

Figure 11 shows the Prophet model's predictions for the test data, with the x-axis representing time from 2004 to 2244 and the y-axis ranging from -400,000 to 600,000 beneficiaries. A blue trend line starts near 0 in 2004 and remains flat, surrounded by a wide light blue confidence interval that widens over time, reflecting increasing uncertainty.

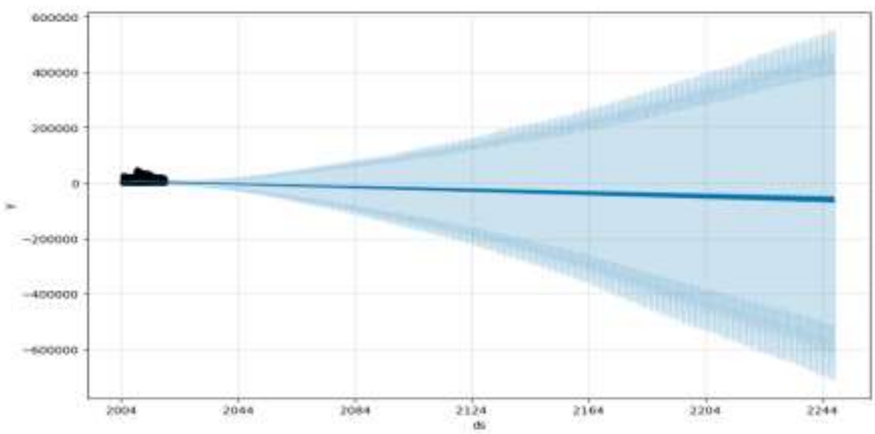

Figure 11. Prophet Model Prediction From Test Data.

4.4 Web-Application Results

Figure 12 shows the home page of the unemployment insurance forecasting application, designed as a user-friendly interface. The page features a clean layout with a header displaying the title "Unemployment Insurance Forecast Tool," a brief welcome message, and navigation links to sections like "About," "Contact Us," and "Predictions." A central banner highlights key statistics, such as "13,760 Records Analyzed" and "Forecasting Since 2001," with a background image of a diverse workforce.

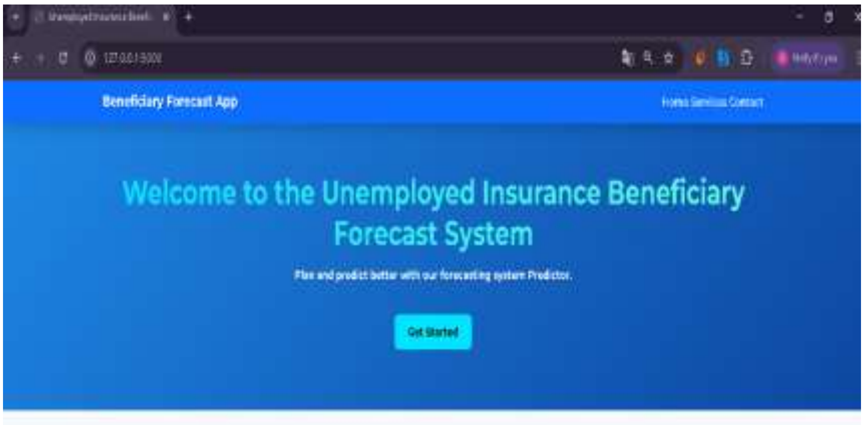

Figure 12. Home Page.

Figure 13 shows the Contact-us page of the forecasting application. The page features a form with fields for Name, Email, Subject, and Message, alongside a contact email (e.g., support@xai.com) and a phone number (e.g., +1-800-555-1234). Additional details include the company address ("xAI, 123 Innovation Drive, CA, USA") and operating hours ("Monday-Friday, 9 AM - 5 PM PST"). A map widget or embedded Google Maps link highlights the location, with a footer containing social media icons (e.g., X, LinkedIn) and a copyright notice ("© 2025 xAI").

Figure 13. Contact-us Page.

Figure 14 shows the prediction input interface of the forecasting model. The page includes a a date picker starting from 2001-01-01 with a default of 2025-07-01, and input fields for historical beneficiary counts (e.g., 1,600) and benefit amounts (e.g., $157,000). Additional options allow users to specify forecast horizons (e.g., 6 or 12 months) and model selection (e.g., Prophet), with a "Submit" button to process the input data for forecasting.

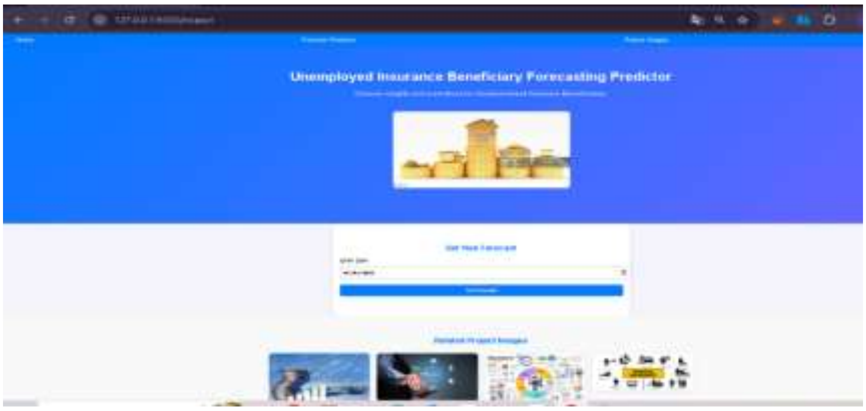

Figure 14. Prediction Input to Model.

Figure 15 shows the prediction output interface with a forecasting graph generated by the model. The page displays a table with predicted beneficiary counts (e.g., 1,650 for August 2025, 1,700 for September 2025), alongside a line graph where the x-axis spans date and the y-axis contains beneficiaries.

Figure 15. Prediction Output with Forecasting Graph From Model.

5. CONCLUSION

In forecasting unemployment insurance beneficiaries, a comparative evaluation of four time series models such as ARIMA, SARIMA, AutoReg, and Prophet was performed using key performance metrics: MSE, MAE, and R^2-Score. Among these, the Prophet model achieved the highest R^2 value of 0.7906, suggesting that it captures the underlying trend and seasonality more effectively than the other models. However, this came at the cost of higher prediction errors, as indicated by its MSE of 14.6705 and MAE of 0.3296, which were significantly larger than those of the other models.On the other hand, ARIMA and AutoReg models produced the lowest MSE of 0.6663 and MAE of 0.0417, indicating their strength in minimizing absolute and squared prediction errors. Their R^2 values, however, were limited to 0.3530, reflecting a weaker capacity to explain total variance in the dataset. SARIMA, which accounts for seasonality, showed slightly better R^2 (0.3658) than ARIMA and AutoReg but still lagged far behind Prophet in capturing complex trends. Thus, while Prophet excels in learning richer temporal patterns, ARIMA and AutoReg are more reliable for consistent error minimization, highlighting a trade-off between model complexity and predictive stability.

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