Future Evolution of Telemedicine: Enhancing Healthcare Accessibility and Reliability through the Integration of Machine Learning Techniques

MSc Research Project
Data Analytics

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Future Evolution of Telemedicine: Enhancing Healthcare Accessibility and Reliability through the Integration of Machine Learning Techniques

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Abstract

The research investigates the future evolution of telemedicine, focusing on enhancing healthcare accessibility through the integration of machine learning techniques. Amidst the COVID-19 pandemic, a four-week survey in the United States was conducted to analyse the increasing trend in telemedicine usage. Utilizing this dataset, the research applies ARIMA, SARIMA, LSTM, and Bi-LSTM models to forecast telemedicine utilization, with Mean Squared Error (MSE) as the error metric for evaluating predictive accuracy. MSE is pivotal in determining the model's precision in forecasting, measuring the average squared difference between predicted and actual values. The ARIMA model, serving as the baseline, registered a higher MSE of 22.2804, revealing its limitations in handling complex data. The SARIMA model showed improvement, reducing the MSE to 17.7817 and demonstrating better capability in addressing seasonal variations. The LSTM model further advanced accuracy, lowering the MSE to 7.1710, indicating its strength in deciphering intricate data patterns. However, the Bi-LSTM model proved to be the most effective, achieving the lowest MSE of 2.3902, which highlights its exceptional ability in forecasting. This signifies an approximately 89.42% increase in accuracy from ARIMA to Bi-LSTM. These findings illustrate that advanced ML models, especially the Bi-LSTM outperforms the to transform telemedicine into a more efficient medical platform.

1. Introduction

1.1 Background

Telemedicine leverages technologies to deliver healthcare services remotely. Its journey, dating back to the late 1900s, reflects a transformation from basic remote consultations to a comprehensive digital healthcare solution. The COVID-19 pandemic accelerated this evolution, showcasing telemedicine's critical role in ensuring continuous healthcare delivery. This period of rapid growth, however, has also highlighted the need for advanced technological integration to meet the increasing demands of modern healthcare systems.

1.2 Importance

The integration of machine learning (ML) in telemedicine represents a crucial step towards addressing current healthcare challenges. Despite its potential, telemedicine's full capabilities are yet to be realized. Advanced ML algorithms promise significant enhancements in disease prediction, data analysis, and resource management. The application of machine learning algorithms stands to revolutionize telemedicine by offering more insights on patient care insights, and more accurate predictions related to health and medicine.

1.3 Research Question and Objectives

Central to this research is the question: ***"How can the integration of time series machine learning techniques elevate telemedicine's impact on healthcare accessibility and reliability?"***

This in-depth study focuses on implementation of time series models, that is ARIMA, SARIMA, LSTM, and Bi-LSTM, applied to a dataset having categorical data. The research explores their effectiveness in forecasting telemedicine usage trends, overcoming current limitations, and it concludes by proposing actionable strategies for the integration of ML into telemedicine, aiming to revolutionise healthcare delivery.

1.4 Limitations

With respect to data scope, the reliance on specific datasets, mainly from the United States, may not fully represent global telemedicine trends. Rapid technological advancements that have fast-paced evolution of machine learning technologies might outpace the current analysis, potentially affecting the long-term applicability of the findings. Different healthcare infrastructures across regions may affect the feasibility of applying the study's recommendations universally.

1.5 Outline of the Report

Section 2 (Related Work): Offers a comprehensive review of existing literature, examining the historical development, challenges, and emerging trends in telemedicine, and setting the stage for the study's context.
Section 3 (Research Methodology): Elaborates on the methodological framework, encompassing data collection, pre-processing, KPSS test for ML models applications. **Section 4 (Design Specification):** Provides an in-depth discussion on the selection of machine learning models, detailing the rationale behind choosing ARIMA, SARIMA, LSTM, and Bi-LSTM, and their relevance to the research objectives.
Section 5 (Implementation): Describes the practical application of the selected models, including the process of model fitting, data analysis, and the interpretation of results. **Section 6 (Evaluation):** Critically assesses the performance of each model, exploring their strengths and limitations in the context of telemedicine forecasting.
Section 7 (Results): Presents the outcomes of the model comparisons, integrating visual and statistical analyses to provide a clear understanding of each model's efficacy.
Section 8 (Findings and Discussions): Reflects on the research findings, discussing their implications for telemedicine and machine learning, and how they address the research question and objectives.
Section 9 (Conclusion): Summarizes the study's key contributions, highlights its significance in the broader context of telemedicine and machine learning, and suggests potential avenues for future research in this evolving field.

2. Related Work

"Over the next 10 years, the healthcare system will change to focus more on preventive medicine and healthcare in the home, with fewer doctors and a new class of home healthcare providers. Healthcare professionals need to debate how best to manage these changes."

- Peter M Yellowlees and Peter M Brooks (1999)

With the quote stated above, this literature review includes various sets of academic databases and papers to represent the current state of research in this field. The papers were chosen to trace the history of telemedicine and highlight the role of technological innovations, particularly Machine Learning, in understanding the prospects of telemedicine and how their techniques can improve its use in the future. The report addresses telemedicine issues including accessibility, diagnostic accuracy, patient involvement, and costeffectiveness. Exploring challenges and growth, our research provides a deeper insight into time series analysis, and at the end of the section we see how the distinctive nature of our research is envisioned to understand the future of telemedicine.

2.1 Background and Challenges of Telemedicine

According to Dr. Liji Thomas, telemedicine has made patient-doctor interactions digital, challenging traditional healthcare. Vuononvirta et al., 2011 explored the conflict between telemedicine's promise and its efficacy and expense. This topic is expanded by Bashshur, Shannon, and Krupinski (2011), who examined telemedicine's resiliency across infrastructure and privacy issues. Iribarne et al. (2020) investigated its use in several medical specializations, whereas Nittari et al. (2020) evaluated its ethical and legal implications in healthcare.

2.2 Growth, Trends, and Overcoming Challenges

Telemedicine has evolved and survived. Bashshur et al. (2018) vividly describe its dramatic rise during COVID-19, altering healthcare. Mehrotra et al. (2021) highlight the growing relevance of telemedicine in mental health, particularly in rural healthcare. Lluch (2011) acknowledges integration issues but highlights outstanding progress toward accessible healthcare. Mars (2013) examines Africa's healthcare revolution and how telemedicine might benefit global health.

2.3 Evolution of Telemedicine from 1990s to 2019

With the increase in technology and devices, telemedicine began during the early 1990s with pioneers like Angaran (1999) and Heinzelmann et al. (2005) who saw a trend toward customized, home-based care. Wang et al. (2019) examined the economic benefits and market dynamics of telemedicine before the pandemic, setting the groundwork for a disruptive healthcare delivery strategy.

2.4 Rise and Extensive Usage During COVID-19

During the outbreak of COVID-19, telemedicine grew its popularity. Bouabida et al. (2021) highlighted Medicaid's rapid adoption of telemedicine, while Nittari et al., 2022 and Panahi (2021) examined its potential to reduce health disparities. Telemedicine's adaptation and resilience in preserving care continuity during worldwide lockdowns are documented by Patel et al. (2021) and Bokolo (2021). Bashshur et al. (2021) and Calton et al. (2020)

emphasized telemedicine's pandemic response and long-term healthcare delivery potential. Telemedicine platforms have improved Virtual Diagnostic Solutions, as seen in Figure 1.

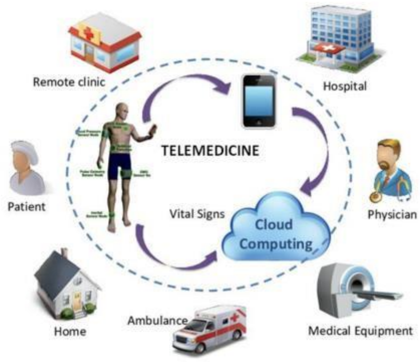

Figure 1: Telemedicine Infrastructure and Components (Image Source)

2.5 Post-pandemic Utilisation of Telemedicine via Machine Learning

Pandya et al. (2021) and Mehrotra et al. (2021) addressed how to validate telemedicine in healthcare. Rubin (2021) promoted cross-state policy coherence. Machine learning opens a new chapter for Dhanya et al. (2022) on telemedicine app user perceptions. Wyld et al. (2022) and Schünke et al. (2022) investigated the relationship between AI and telemedicine, highlighting revolutionary changes in diagnoses and patient monitoring and presenting a future where healthcare relies increasingly on data.

2.6 Time Series Analysis in Telemedicine

Bouslama et al.'s latency-driven data controller in Spark Streaming aligns with our focus on managing temporal variability in telemedicine. Similarly, Wang et al.'s approach lies in leveraging image encoding and tiled CNNs for time series classification. With the forthcoming section, we detail our research for cleaning and modelling the dataset to see how time series analysis in telemedicine for utilising models like ARIMA, SARIMAX, LSTM and Bi-LSTM shall be evaluated and discussed.

3. Research Methodology

This section provides a guide through the procedural steps from data collection to advanced data modelling. The methodology for data preparation and pre-processing adopted in this study is depicted in the provided flowchart in figure 2.

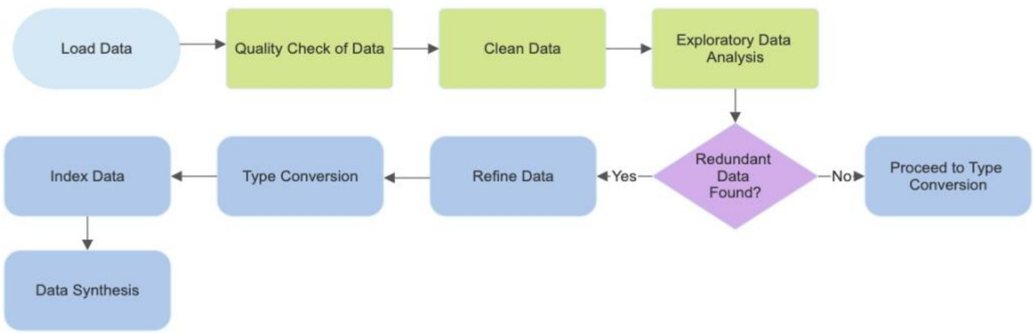

Figure 2: Workflow Diagram of Data Pre-processing

3.1 Data pre-processing

3.1.1 Data Loading

The dataset, Telemedicine Use in the Last 4 Weeks was sourced from the Household Pulse Survey conducted by the *National Center for Health Statistics (NCHS).* The U.S. Census Bureau, in partnership with federal agencies, initiated the Household Pulse Survey to capture pandemic impacts on U.S. households. As conducted online, it gauges effects on employment, spending, food security, housing, education, and wellness, ensuring accurate and timely estimates. This dataset captures recent changes, aligning with the survey's focus on assessing the impact of the COVID-19 pandemic on the aspect of utilising accurate and timely estimates, making it well-suited for analysing telemedicine usage trends.

3.1.2 Data Cleaning

We focused on identifying and handling missing values. This was accomplished using the ***isnull().sum() method.*** As seen in the left-hand side of figure 3, we observe the that out of 13 columns, 9 columns having missing values, we consider columns to be removed with a percentage of 60, where we make an assumption that more than the 60% missing values were removed to maintain a balance between data integrity of the dataset with a threshold of 0.6. With this process, *'Quartile Range'* and *'Suppression Flag'* were removed, as they were irrelevant for our analysis, due to redundancy and lack of critical importance for our research objectives.

```
Indicator                   0
Group                       0
State                       0
Subgroup                    0
Phase                       0
Time Period                 0
Time Period Label           0
Time Period Start Date      0
Time Period End Date        0
Value                     240
Low CI                    240
High CI                   240
Confidence Interval       240
Quartile Range           1202
dtype: int64
```

```
Indicator                 0
Group                     0
State                     0
Subgroup                  0
Phase                     0
Time Period               0
Time Period Label         0
Time Period Start Date    0
Time Period End Date      0
Value                     0
Low CI                    0
High CI                   0
Confidence Interval       0
dtype: int64
```

Figure 3: Comparative Overview of Dataset Integrity Pre- and Post-Cleaning

3.1.3 Exploratory Data Analysis (EDA)

This step involved a detailed examination of various categorical variables in the dataset. We used bar horizontal plots to visualize categories like *'Indicator', 'Group', 'State', 'Subgroup',* and *'Phase'*. This process helped us understand the distribution and frequency of these categories, providing insights into the dataset's composition. One such bar plot is as shown in figure 4, adults who utilised telemedicine and children who utilised telemedicine in the dedicated time frame.

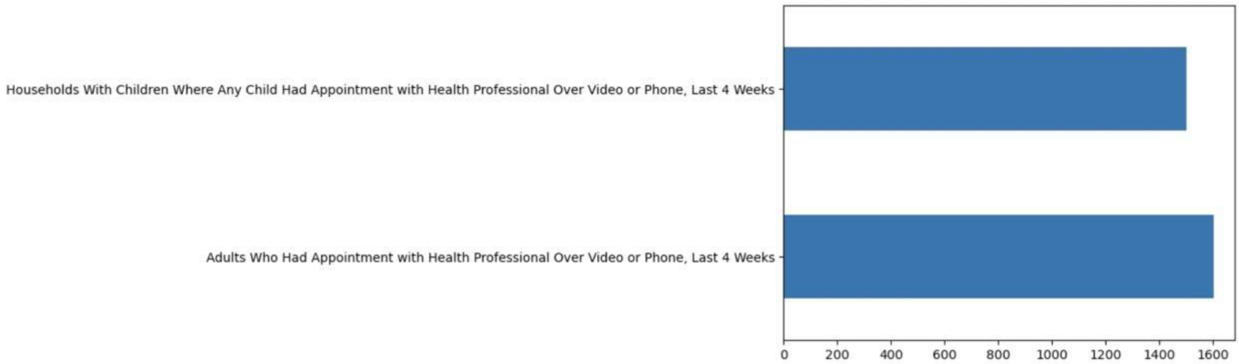

Figure 4: Comparative Bar Chart with Indicators of Telehealth Appointments in Households with Children Versus Adults Over a Four-Week Period

3.1.4 Data Refinement

After EDA, data refinement was performed that included streamlining the dataset by removing columns such as *'Time Period Label', 'Time Period End Date', and 'Confidence Interval'* as shown below in figure 5. These columns were not essential for our analysis objectives.

	Indicator	Group	State	Subgroup	Phase	Time Period	Time Period Start Date	Value	Low CI	High CI
0	Adults Who Had Appointment with Health Profess...	National Estimate	United States	United States	3.1	28	04/14/2021	25.7	25.0	26.4
1	Adults Who Had Appointment with Health Profess...	By Age	United States	18 - 29 years	3.1	28	04/14/2021	21.6	19.2	24.1
2	Adults Who Had Appointment with Health Profess...	By Age	United States	30 - 39 years	3.1	28	04/14/2021	23.1	21.7	24.5
3	Adults Who Had Appointment with Health Profess...	By Age	United States	40 - 49 years	3.1	28	04/14/2021	25.7	24.2	27.3
4	Adults Who Had Appointment with Health Profess...	By Age	United States	50 - 59 years	3.1	28	04/14/2021	26.3	24.6	28.1

Figure 5: Streamlined Telemedicine Dataset Post-Refinement for Analysis

3.1.5 Type Conversion

We transformed the *'Time Period Start Date'* column from an object type to a *datetime* format as shown below in figure 6. This conversion facilitated time-based analysis and was critical for subsequent time-series analysis that we intent to.

Figure 6: Transformation of 'Time Period Start Date' Column to Datetime Type in Pandas DataFrame

3.1.6 Indexing Data

The refined *'Time Period Start Date'* column was then set as the DataFrame index, organizing the data chronologically. This allowed for more intuitive access of time-series data within the dataset.

3.1.7 Data Synthesis

Throughout the pre-processing phase, we ensured that all time related patient records and survey data were retained. The aim was to synthesize the dataset by including only the most accurate information for forecasting of the analysis. This synthesis ensured that each entry in the dataset contributed valuable insights for our research. The data pre-processing to convert categorical data into a machine-readable numerical data format ensures the ethical consideration to protect patient privacy and avoid retaining sensitive customer data that could be traced back to individuals. In figure 7, the dataset summary is presented post the preprocessing which showcases all the retained columns, ML-applicable data types, and the absence of NaN (Not a Number) values. This curated dataset is now primed for the application of time series models.

```
data.info()

<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 3104 entries, 2021-04-14 to 2022-07-27
Data columns (total 9 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Indicator    3104 non-null   int64
 1   Group        3104 non-null   int64
 2   State        3104 non-null   int64
 3   Subgroup     3104 non-null   int64
 4   Phase        3104 non-null   float64
 5   Time Period  3104 non-null   int64
 6   Value        3104 non-null   float64
 7   Low CI       3104 non-null   float64
 8   High CI      3104 non-null   float64
dtypes: float64(4), int64(5)
memory usage: 242.5 KB
```

Figure 7: Concise summary of dataset after performing data pre-processing

3.2 Time Series Analysis

The research aims to forecast telemedicine utilization over time, necessitating a time series analytical approach. This approach is particularly suited to our dataset, which chronicles the evolving usage patterns of telemedicine, as it can analyse the underlying trends, seasonalities, and temporal dynamics of telemedicine use which are critical in interpreting how telemedicine usage has changed and might change in the future.

3.2.1 KPSS Test for Stationarity

The KPSS (Kwiatkowski-Phillips-Schmidt-Shin) test was applied to the 'Value' column to check for stationarity, which is a critical assumption in time-series analysis. A visual examination of autocorrelation and partial autocorrelation plots was also conducted. Following the comprehensive data pre-processing phase, we advance to the next stage of time series analysis that is the assertion of stationarity within our data, which is a prerequisite for the reliability of our predictive models. The rationale for the KPSS test is grounded in its ability to interrogate the series for any presence of unit roots, that is the indicators of nonstationarity. The execution of the KPSS test proceeds as follows depicted on the flowchart below:

1. **Computation of the KPSS Statistic:** The statistic is calculated as a measure of stationarity, indicating how strongly the series is defined by a trend.
2. **P-Value Assessment:** The p-value offers a significance test of the KPSS statistic, with values below 0.05 typically rejecting the null hypothesis of stationarity.
3. **Lag Selection:** The number of lags used in the test is determined based on the data to account for serial correlation.
4. **Critical Value Comparison:** The KPSS statistic is compared with critical values at conventional significance levels to confirm or deny stationarity.

The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots provided a visual inspection of correlations. The flowchart in figure 8 below shows the time series analysis process flow using KPSS test and data segmentation into train and test sets.

Figure 8: Flowchart of Time Series Analysis Process Using KPSS Test and Data Segmentation

Time series models cannot handle NaN values and require complete datasets for accurate forecasting. Before training the models, NaN values must be addressed either through imputation, which involves estimating the missing values based on available data to maintain the continuity of the time series. . According to solutions to missing data (Haitovsky 1968), *kpss_test(data['Value'].diff().dropna())* is used on the differenced 'Value' column of a DataFrame, after removing NaN values, which helps determine if the series is stationary or if it exhibits trends or seasonality. The KPSS test initially indicated that the 'Value' time series was non-stationary, likely due to the presence of trend and seasonality, as suggested by a KPSS Statistic significantly larger than the critical values and a low p-value. To achieve stationarity, a common approach is to apply differencing to the data. This involves subtracting the previous observation from the current observation. When the differencing operation *data['Value'].diff().dropna()* was applied to the series, the subsequent KPSS test yielded a much lower KPSS Statistic and a higher p-value, which fell above the critical values. This indicates that the differenced series does not have a unit root and can be considered stationary. This transformation is evident in the ACF and PACF plots (Figure 9 and Figure 10), where the autocorrelations of the differenced series dropped off more quickly compared to the original series, further suggesting the achievement of stationarity. This assessment was conducted in two stages. Initially, the KPSS test revealed that the original series did not meet the stationarity criterion ***(KPSS Statistic: 3.023; p-value: 0.01)***, implying the influence of trend and seasonal components. Subsequently, a differencing transformation was applied, which is a standard remedy for removing such non-stationary elements. The differenced series passed the KPSS test ***(KPSS Statistic: 0.032; p-value: 0.10)***, suggesting successful mitigation of the non-stationary properties.

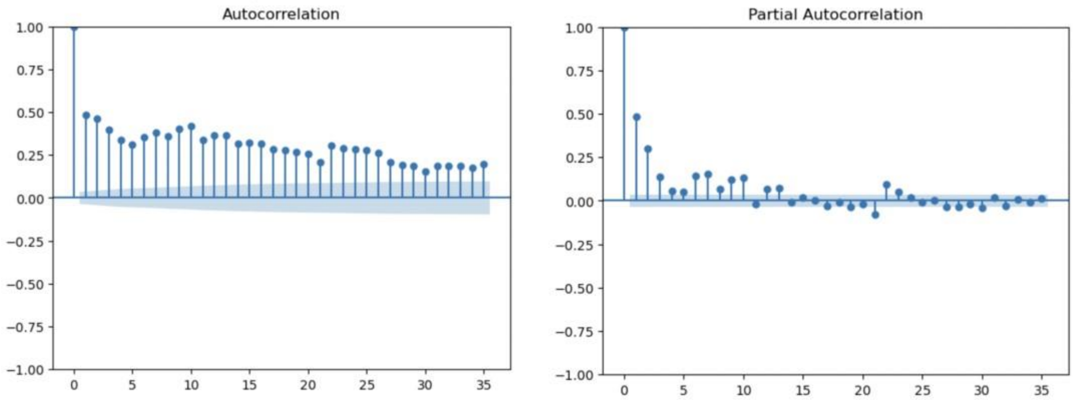

Figure 9: Autocorrelation Function (ACF) Plot and Partial Autocorrelation Function (PACF) Plot of Differenced Time Series

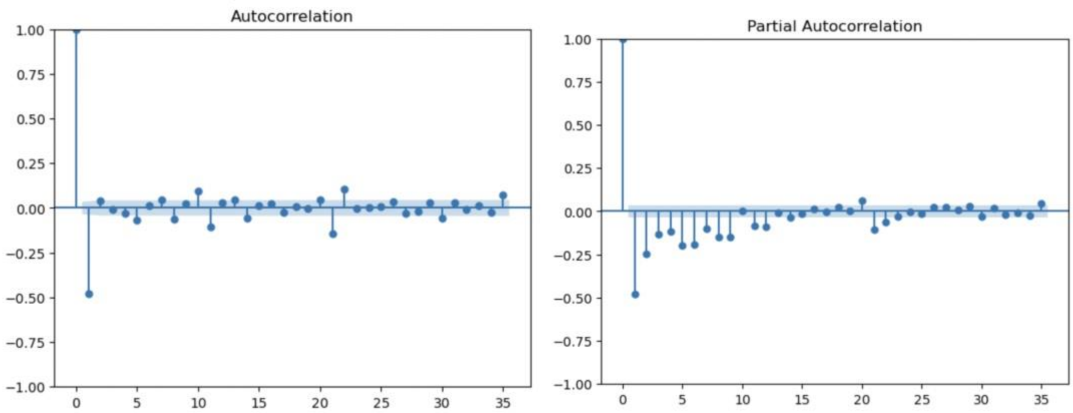

Figure 10: Autocorrelation Function (ACF) Plot and Partial Autocorrelation Function (PACF) Plot for Stationarised Time Series

The KPSS (Kwiatkowski-Phillips-Schmidt-Shin) test was first performed to 'Value' column of the dataset to assess stationarity. The test showed non-stationarity with a KPSS Statistic of *3.023199187659166* and a p-value of *0.01*. These findings, especially the KPSS Statistic being over the critical thresholds (10%: 0.347, 5%: 0.463, 2.5%: 0.574, 1%: 0.739), indicated data trends or seasonality. In time series analysis, non-stationarity can lead to misleading results because most forecasting models assume a consistent mean, variance, and autocorrelation. Our differencing code was *data['Value'].diff().dropna()*, with which by removing data changes, differencing stabilizes the mean of time series thus eliminating trend and seasonality implications. This task turns the data into a series of changes from one period to the next. When we reapplied the KPSS test on this differenced series, the KPSS Statistic decreased to *0.03154485283141166* and the p-value rose to *0.1*. The differenced series does not reject the null hypothesis of stationarity because this new KPSS Statistic is considerably below the critical values and has a larger p-value. Thus, differencing makes the series stationary. Time series forecasting relies on stationary data to keep model parameters constant, resulting in more accurate forecasts. The differencing technique's impact on KPSS test results shows that our dataset has stabilized, preparing us for the next phase of our research.

3.2.2 Data Segmentation

Upon establishing stationarity, the dataset was segmented into training and testing sets. A methodical approach was taken, preserving the final **52** observations (28 lags observed in stationarity test, 52 for train and test sets) to provide an unbiased assessment of the forecasting model's performance.

```
KPSS Statistic: 3.023199187659166
p-value: 0.01
num lags: 28
```

Figure 11: Number of lags in non-stationary KPSS test

3.2.3 Model Preparation

Once we established segmentation, the data was partitioned into independent variables (X) and the dependent variable (Y), laying the groundwork for the application of predictive modelling techniques. The shapes of these datasets were duly recorded, ensuring congruence between the number of observations and the corresponding variables. A placeholder DataFrame named 'score' was created to serve as a repository for model evaluation metrics, encapsulating the performance of various forecasting algorithms like ARIMA, SARIMAX, LSTM, and Bi-LSTM where we will examine how each of these models uses the stationary character of our dataset to make accurate forecasts.

4. Design Specification

The design specification section provides an overview of the flow in figure 12 that has been followed throughout the research. Firstly, the telemedicine dataset was obtained from the Centers for Disease Control and Prevention catalogue. Subsequently, data pre-processing involved quality checks, cleaning, and refinement, ensuring stationarity through the KPSS test and differencing in time series analysis. The dataset was then segmented for training and testing sets, preparing for the application and evaluation of models (ARIMA, SARIMAX, LSTM, Bi-LSTM). The subsequent section details the implementation of time series models, evaluating performance metrics, and interpreting results for telemedicine usage.

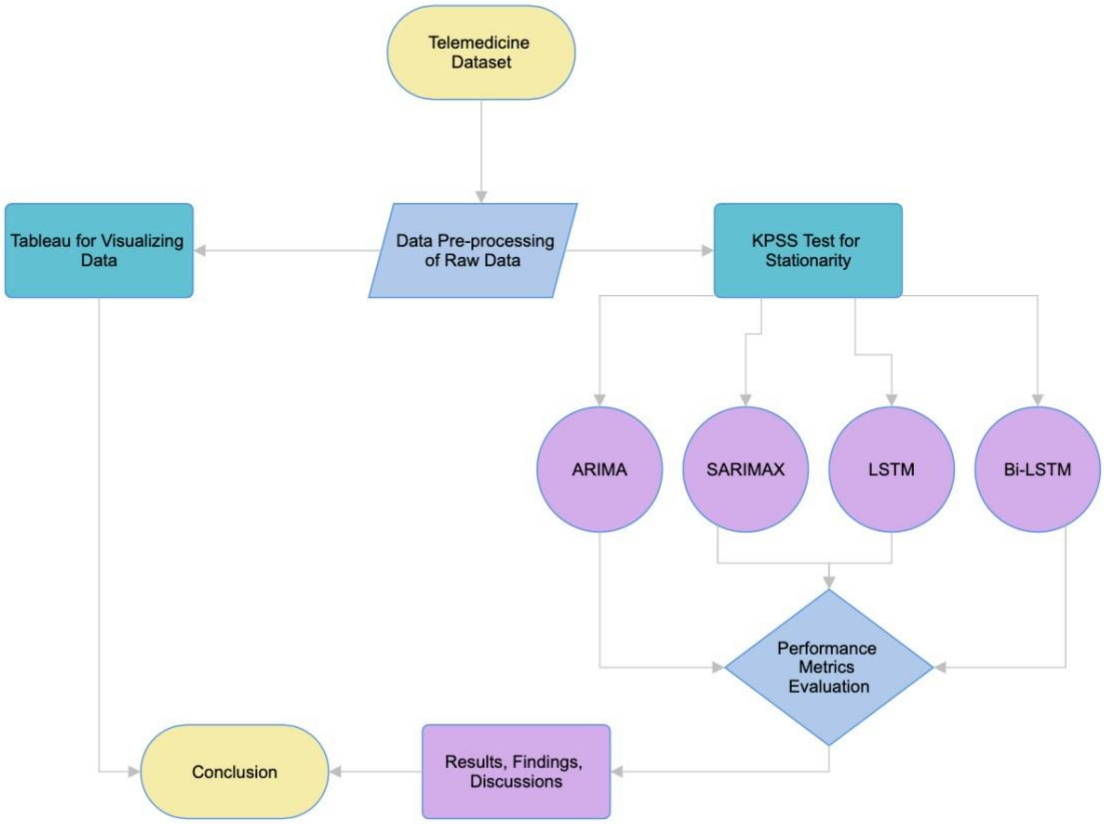

Figure 12: Design Workflow of Telemedicine Data Analysis from Pre-processing to Model Evaluation and Conclusion

5. Implementation

In time-series analysis, the ARIMA model is characterized by three parameters: p, d, and q. The parameter p represents the number of autoregressive terms, d indicates the degree of differencing involved, and q corresponds to the number of moving average terms. These parameters are pivotal in capturing the dependencies and dynamics of time-series data. The selection of these values is based on diagnostic tests and autocorrelation analyses, ensuring that the model captures the underlying patterns in the data effectively.

5.1 Data Pre-processing for Time-Series Forecasting Models

Data pre-processing is a critical step in the implementation of time-series forecasting models. For the ARIMA and SARIMAX models, pre-processing involved ensuring the data was stationary, a fundamental requirement for these statistical models. The KPSS test was employed on the 'Value' time series to identify trends and seasonality. In the case of the LSTM and Bidirectional LSTM models, pre-processing took a different turn. The data had to be converted into a three-dimensional array format that these neural networks require. This was achieved by reshaping the data into the form (samples, time steps, features) using NumPy's 'reshape' function. In our approach, we have chosen error metrics, such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) to evaluate the performance of our forecasting models. We emphasise that a lower Mean Squared Error (MSE) corresponds to higher forecasting accuracy enabling a comprehensive analysis of ARIMA, SARIMA, LSTM, and Bi-LSTM models for evaluating telemedicine forecasting precision.

5.1.1 ARIMA Model

The ARIMA (28, 1, 20) model fitting on 3052 observations was our first attempt. These values are chosen based on the time series characteristics, like 28 lags and a noticeable change in ACF and PACF plots after 20 lags and a differential of 1. The high AIC and BIC values suggested a complex model, but the tests showed the residuals were independent and normally distributed, which is good. Forecast comparisons and visualizations showed some discrepancies between expected and actual values, recommending improvement.

5.1.2 SARIMA Model

We added the SARIMA (28, 1, 20)x(0, 1, [1, 2], 28) model to account for seasonality in our time-series analysis. This seasonal order indicates that there is a seasonal moving average component (2) with a seasonal period of 28. The value of 0 for the seasonal autoregressive order (P) indicates that there is no seasonal autoregressive component. So, while the autoregressive and differencing components may resemble those in ARIMA, the focus is on seasonal differencing (D), seasonal moving average (Q), and the seasonal period (S) of 28 time units. so SARIMAX suggests a pattern that repeats every 28 observations. The model's structure was sophisticated, having non-seasonal and seasonal components to capture trends and seasonal changes. Although several coefficients were not statistically significant, the lower AIC and BIC values compared to the ARIMA model showed a better match. Performance measures showed higher accuracy over the ARIMA model, highlighting the importance of seasonal impacts in healthcare forecasting.

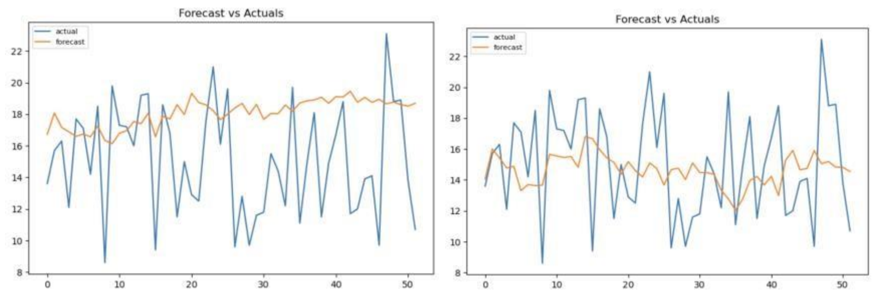

Figure 13: ARIMA and SARIMA Model Forecast versus Actual Time Series Data

5.1.3 LSTM Model

The architecture of LSTM is configured with multiple layers, specifying units, activation functions, and dropout rates. The model is compiled with mean squared error as the loss function. It is trained on the training set (X_train, Y_train) for 10 epochs. The model's robustness was shown by its decreasing loss throughout training epochs and its improved test set performance, as shown by the lowest MSE.

5.1.4 Bi-LSTM Model

Finally, the Bi-LSTM model processed data in both forward and backward time orientations, improving temporal understanding. Its superior predictive power was shown by its lower loss and error metrics during training and top test set performance. The comparative analysis of ACF and PACF plots across the ARIMA, SARIMA, LSTM, and Bi-LSTM models provides a multifaceted view of time-series forecasting. These plots serve as a visual tool for understanding the correlation structure of the data and the lags that significantly influence the models. For ARIMA and SARIMA, the plots help fine-tune the (p, d, q) parameters and seasonal components, ensuring the models are attuned to the inherent seasonality and trends. After thoroughly analysing each model's performance measures and found that as we proceeded from ARIMA to Bi-LSTM, our forecasts improved, which is crucial in telemedicine for resource allocation, demand prediction, and service optimization.

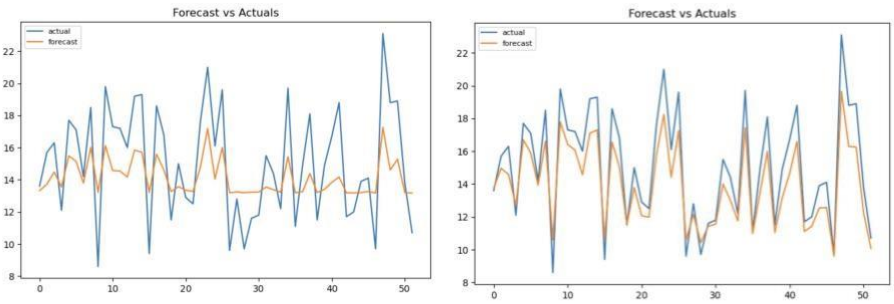

Figure 14: LSTM Model and Bi-LSTM Model Forecast versus Actual Time Series Data

	Actual	ARIMA-Forecast	SARIMA-Forecast	LSTM-Forecast	BiLSTM-Forecast
0	13.6	16.723493	14.061869	13.318880	13.751727
1	15.7	18.075831	16.004282	13.731413	14.962646
2	16.3	17.164976	15.426370	14.479886	14.588446
3	12.1	16.881986	14.779974	13.548525	12.692090
4	17.7	16.599406	14.877376	15.489600	16.699663
5	17.1	16.741111	13.303576	15.140324	15.890475
6	14.2	16.573833	13.697488	13.791762	13.933333
7	18.5	17.249513	13.635682	16.017929	16.613453
8	8.6	16.339876	13.664702	13.212348	10.598732
9	19.8	16.134869	15.663257	16.130697	17.795034

Figure 15: Comparative Forecast Results of ARIMA, SARIMA, LSTM, and Bi-LSTM Models

	0	1	2	3
0	ARIMA	22.280399	4.720212	3.823641
0	SARIMA	12.781661	3.575145	2.974683
0	LSTM	7.171037	2.677879	2.348136
0	Bidirectional LSTM	2.390244	1.546042	1.323637

Figure 16: Error Metrics Comparison Across ARIMA, SARIMA, LSTM, and Bi-LSTM Models

6. Evaluation

Tableau visualization helps us interpret telemedicine usage data in the evaluation phase. Figure 17 shows telemedicine usage comparison over discrete time periods in bubble and pie charts, providing statistical confidence. The bubble chart on the left side in figure 17 displays telemedicine usage over discrete time periods. Each bubble's size is proportional to the value of telemedicine usage during that specific time period, with larger bubbles indicating higher usage.

6.1 Visualisation

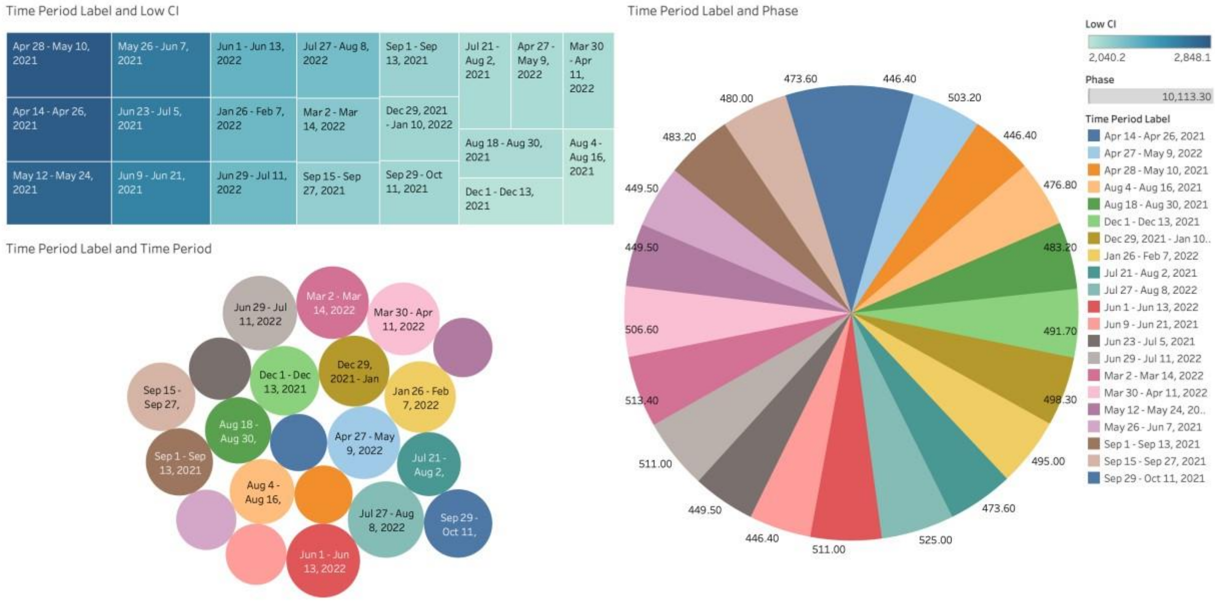

Figure 17: Comparative Visual Analysis of Telemedicine Usage: Bubble Chart of Usage by Time Period and CI, and Pie Chart Distribution by Phase

The pie chart on the right side represents the distribution of telemedicine usage across different phases of a time period. Each slice of the pie corresponds to a distinctive time period, with its area representing the proportion of telemedicine usage in that phase. The colour coding matches each time period label with its corresponding slice in the pie chart.

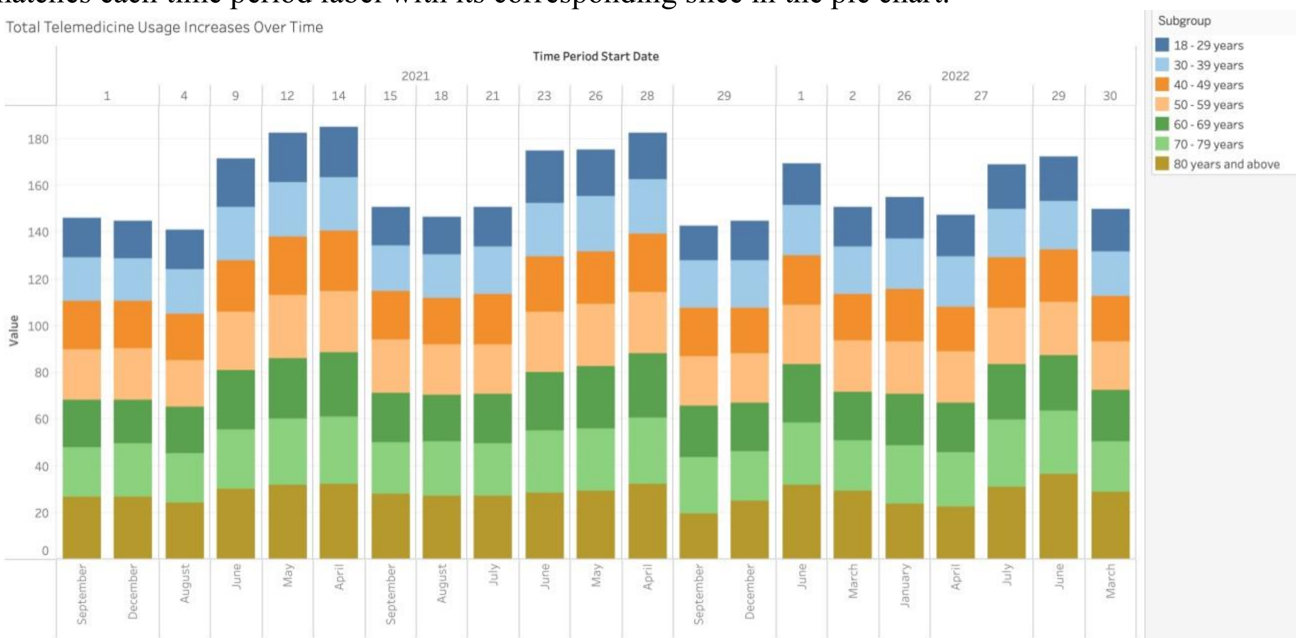

Figure 18: Age-Segmented Telemedicine Utilization Trends Over Time

The graph in Figure 18 depicts the escalation of telemedicine use, segmented by age in the Subgroup, distinctively over dates, months, and years. Each colour within the bars corresponds to a specific age demographic, illustrating the proportional use within each group. The most notable uptick is observed in the '80 years and above' segment, indicating a significant pivot to telemedicine among the elderly. The bar chart in Figure 19 presents two sets of telemedicine usage data over several time periods, distinguished by colour: orange for households with children and blue for adults. Each bar represents a four-week span, with the percentage of the two subgroups who had a health professional appointment via video or phone. The bar plot shows a maximum of 4% higher telemedicine usage among adults compared to households with children. This could reflect differing healthcare needs or accessibilities between these groups.

Figure 19: Distribution of Telemedicine Indicators Over Time Periods

7. Results

Building upon the visual insights, the results section undertakes a numerical examination of forecasting models, as detailed in the below table. This table provides error metrics (MSE, RMSE, MAE) for ARIMA, SARIMA, LSTM, and Bi-LSTM models, providing a quantitative foundation for the analysis. Each model's distinct strengths and weaknesses become apparent, setting the stage for a concise exploration of their individual contributions to telemedicine forecasting. The subsequent subsections dissect the performances, revealing the superior accuracy of the Bi-LSTM model.

7.1 Error Metrics Performance

After testing all models, the Bi-LSTM was the most accurate, suggesting it could be the best telemedicine predicting model. ARIMA's basic insights, SARIMA's seasonal adjustments, and LSTM's deep learning finesse each contributed to our grasp of healthcare time-series forecasting. The examination and findings show that the Mean Squared Error (MSE) reductions across ARIMA, SARIMA, LSTM, and Bidirectional LSTM models demonstrate significant accuracy improvements, with percentages ranging from approximately 12.54% to 81.02%, reinforcing their effectiveness in forecasting telemedicine trends. The Bi-LSTM model's grasp of bidirectional methodology in temporal data makes it an advanced prediction tool for telemedicine as it can learn from past and future data points concurrently, making it a demand forecasting time-series model. Figure 20 provides the comparative analysis of all the models.

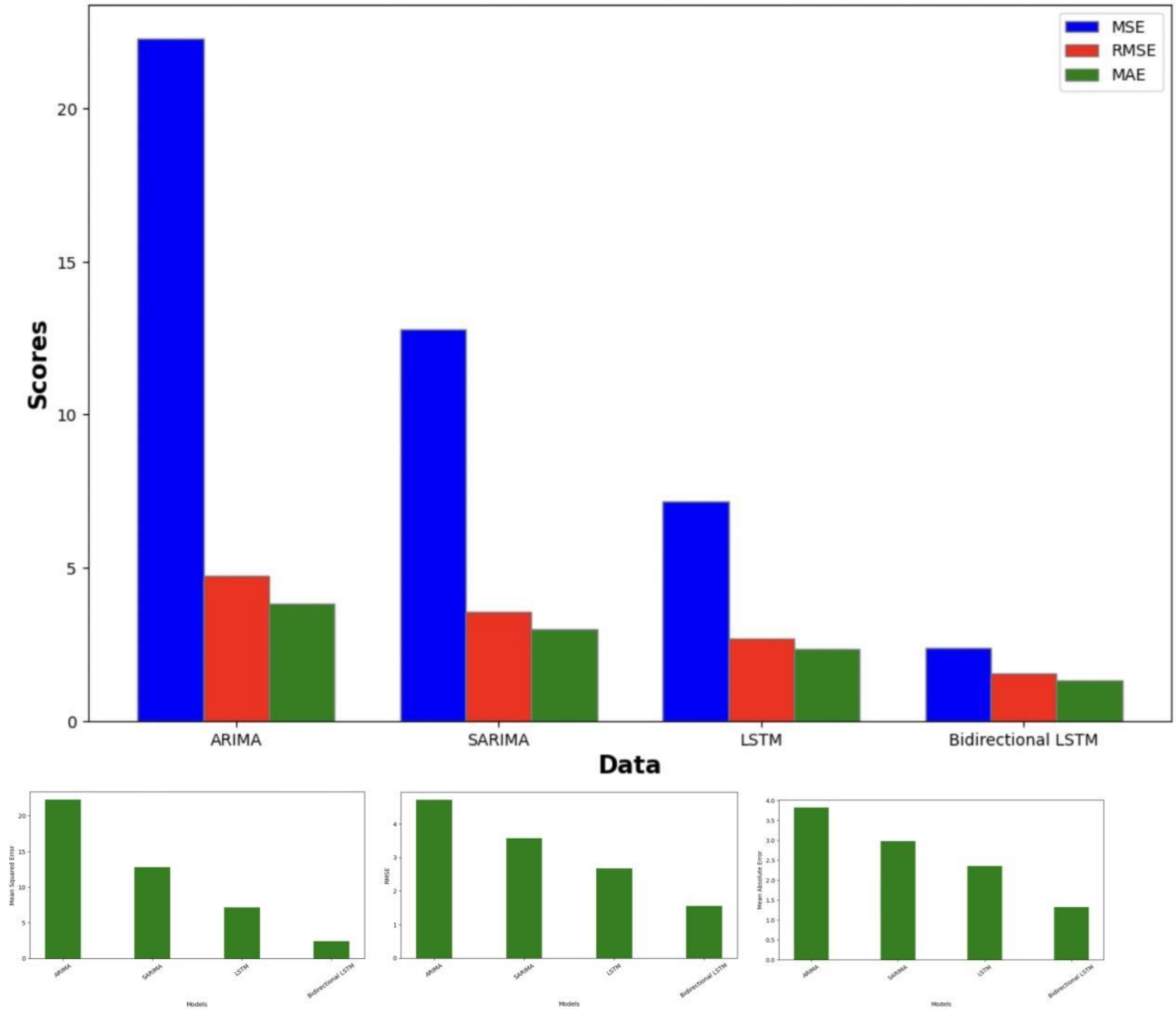

Figure 20: Comparative Analysis of Forecasting Performance for ARIMA, SARIMA, LSTM, and Bi-LSTM Models

7.2 Comparative Analysis

On comparing the performances of each of the time series models, we summarise the results through the table below, that synthesizes the performance of four distinct time-series forecasting models, highlighting their efficacy in predicting telemedicine-related metrics as tabled below in Table 1.

Model	Mean Squared Error	Root Mean Squared Error	Mean Absolute Error
ARIMA	22.2804	4.7202	3.8236
SARIMA	17.7817	3.5751	2.9747
LSTM	7.1710	2.6779	2.3481
Bidirectional LSTM	2.3902	1.5460	1.3236

Table 1: Error Metric Comparison for ARIMA, SARIMA, LSTM, and Bi-LSTM Forecasting Models

1. **ARIMA:** With an MSE of 22.2804, RMSE of 4.7202, and MAE of 3.8236, the ARIMA model has the highest error metrics, suggesting it is the least precise among the four models for this dataset.
2. **SARIMA:** The improved scores with an MSE of 17.7817, RMSE of 3.5751, and MAE of 2.9747 indicate that incorporating seasonality through SARIMA yields better forecasting accuracy than ARIMA.
3. **LSTM:** The LSTM model shows a marked decrease in error metrics (MSE of 7.1710, RMSE of 2.6779, and MAE of 2.3481), reflecting its superior capability to capture complex, non-linear patterns in the data.
4. **Bidirectional LSTM:** The lowest scores across all metrics (MSE of 2.3902, RMSE of 1.5460, and MAE of 1.3236) demonstrate that the Bidirectional LSTM model outperforms the others significantly, offering the most precise forecasts for the telemedicine data.

The transition from ARIMA to SARIMA resulted in a roughly 20.2% increase in accuracy, while the shift from SARIMA to LSTM marked an approximately 59.8% improvement. Moving from LSTM to Bi-LSTM saw a significant jump, yielding around 66.6% higher accuracy. The cumulative accuracy improvement from ARIMA to Bi-LSTM is approximately **89.42%.**

The line chart in Fig 21 compares the performance of four forecasting models against actual telemedicine metrics. The ARIMA model shows the largest deviation, while SARIMA improves on this, suggesting better handling of seasonality. The LSTM model's predictions are closer to the actual data, and the Bi-LSTM model's forecasts align most closely with the actual 'Value' Column, confirming its superior accuracy as indicated by its lowest error metrics (MSE, RMSE, MAE). The graph solidifies the quantitative analysis, showing that the Bi-LSTM model is not only statistically superior but also practically more aligned with the actual data trends.

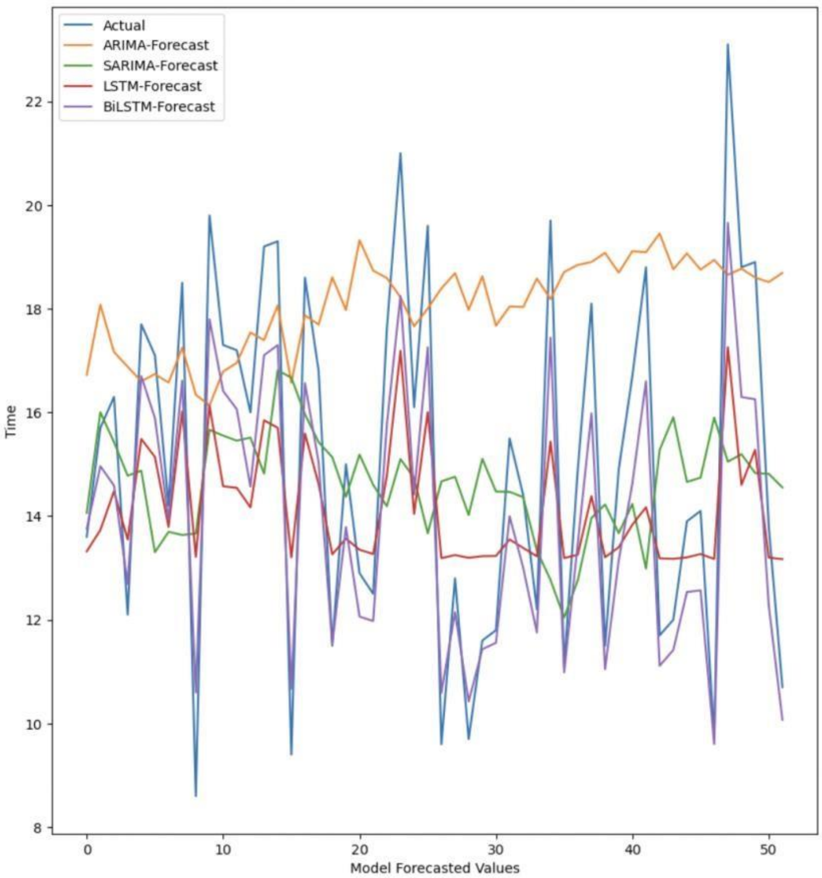

Figure 21: Comparative Forecasting Accuracy of ARIMA, SARIMA, LSTM, and Bi-LSTM Models Against Actual Telemedicine Data

8. Findings and Discussions

Advanced Machine Learning in Telemedicine Forecasting by employing ARIMA, SARIMA, LSTM, and Bi-LSTM models has not only addressed the gaps identified in the existing literature but also set new benchmarks in forecasting accuracy. Notably, the BiLSTM model outperformed the other models with the lowest Mean Squared Error (MSE), a finding that aligns with the growing emphasis on sophisticated data analysis techniques in healthcare, as suggested by studies like Pandya et al. (2021) and Wyld et al. (2022). The BiLSTM model, with its lowest MSE, demonstrated superior performance compared to the traditional ARIMA model, echoing the findings of Rubin (2021) and Schünke et al. (2022) on the potential of advanced analytical techniques in telemedicine. Our study extends the discussions initiated by authors like Dr. Liji Thomas, Vuononvirta et al., and Bashshur et al., who have laid the foundation in understanding the challenges of telemedicine utilisation by employing cutting edge technology. Although many concerns are raised regarding the limitations and future research, this research acknowledges limitations due to the primary reliance on U.S. datasets, as highlighted by Iribarne et al. (2020) and Nittari et al. (2022). The rapid evolution of machine learning technologies, as discussed by Dhanya et al. (2022), also poses a challenge to the long-term applicability of these findings.

9. Conclusion

This research project offers a thorough examination of the field's expanding importance in the world's healthcare organization. The study investigates how telemedicine might be revolutionized by time series models. The study demonstrates the effectiveness of machine learning approaches, particularly the Bi-LSTM model, in precisely predicting patterns of telemedicine utilization through a comprehensive assessment of multiple forecasting models. The study's conclusions highlight how important telemedicine is to improve the accessibility and dependability of healthcare, especially considering international emergencies like the COVID-19 pandemic. It shows a future in which machine learning-enabled telemedicine serves as a platform for effective and individualized patient care for delivering healthcare. The study highlights the necessity for ongoing innovation and the implementation of cuttingedge technologies in healthcare and offers insightful information for researchers and healthcare practitioners. This research project establishes the foundation for ongoing investigations in this area with the goal of advancing telemedicine and a hope for improving the quality of healthcare services around the globe.

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Thesis Questionnaire

Question 1:

What is meant by the quality check of data in Figure 2 and how this feature is carried out in implementation?

Answer:

The Quality check of data step that is mentioned in the flowchart in Figure 2 is just to ensure that the data is loaded correctly and the steps taken are to view data information and printing the top few of the data.

Question 2:

Can you elaborate on what Figure 13 and Figure 19 represent? How about the description of Figure 15 and Figure 16?

Answer:

- Figure 13 shows the graph of forecasted value and actual values for ARIMA and SARIMA models. The graph shows actual values of the telemedicine growth data in the blue line and the orange line shows the forecasted values in by the models ARIMA and SARIMA in their respected graphs. The graph of the forecasted values is not that close to the actual values but the trend is getting captured in the slopes of the graph.
- Figure 15 shows the table of the actual and forecasted values of all the models. The Actual column shows the actual value and the forecast value column followed by the model names is the forecast value for the respective models. The forecast is taken for time period of 10 time steps.
- Figure 16 shows the models performance table. In the later section of the code the column names are added in the table. The first column is the name of the Models, second column represents the Mean Squared Error score, third column represents the Root Mean Squared Error(RMSE) and last and fourth column represents the Mean Absolute Error.
- Figure 19 shows two sets of telemedicine usage data over several time periods, distinguished by colour: orange for households with children and blue for adults. Each bar represents a four-week span, with the percentage of the two subgroups who had a health professional appointment via video or phone. The bar plot shows a maximum of 4% higher telemedicine usage among adults compared to households with children. This could reflect differing healthcare needs or accessibilities between these groups.

Question 3:

How about the fine-tuning of parameters (p,d,q) in the ARIMA model? What parameters are considered in other models?

Answer:

The values for p (autoregressive), d (differencing) and q (moving average) in ARIMA (Autoregressive Integrated Moving Average) and SARIMA (Seasonal ARIMA) model are not tuned they are fixed values considering the lags and stationarity of the data. The value of d is based on the stationarity of the data. We have used KPSS statistic test to check for data stationarity. The test showed that the series os not stationary, so we took the first differential to make the series stationary. To find the values of p and q, Autocorrelation and Partial Autocorrelation plots are generated. They are shown in Figure 9 and 10 in the report. Figure 9 shows the graph before differential and Figure 10 show the graphs after differential is taken on the data. The significant lags that decay slowly in the ACF plot (indicating autoregressive components, AR) and PACF plot (indicating moving average components, MA) gives out the values of p and q.

All the models have different hyperparameters that are mentioned below:

1. SARIMA: other than order which is (p,d,q) same as in Arima it also considers Seasonality order (P, D, Q, s). P is the order of the seasonal autoregressive, D is the seasonal differencing, Q is seasonal moving average component and s is seasonal period or the number of time steps in each season. In our data the number of time steps is 28 days as each data is 4-week record of telemedicine.
2. LSTM: The hyperparameters of LSTM are units=128, activation = 'relu', return_sequences = True, input_shape = (8,1). The units are the number of memory cells in LSTM, ReLU is the activation function that adds non-linearity by setting the input for positive values and zero for negative values, return_sequences =True is used to stack multiple LSTM layers on top of each other and input shape is the shape of the input data.
3. Bidirectional LSTM used the same LSTM hyperparameters. The difference lies in the bidirectional nature of the Bi-LSTM. By this we mean the model trains in both ways forward feeding and backward propagation.

Question 4:

Briefly present how your research outcome aligns with the current research in the telemedicine field that make use of time series machine learning techniques.

Answer:

While current studies primarily focus on trend analysis and the impact within hospital settings, our research takes a distinct approach where we concentrate on driving growth in the field of medicine, specifically by forecasting future telemedicine orders. With technological advancements and growth trends from our study, we employ machine learning models such as ARIMA, SARIMAX, LSTM, and Bi-LSTM. These are time series models that contribute on data-driven healthcare solutions. Our approach stands to provide a broader vision for the future of healthcare that could be preventive medicine, home healthcare, and all of this to be achieved using Machine Learning.

Question 5:

Describe the process that was followed in the segmentation of the dataset into two sets for training and testing.

Answer:

The data segmentation into train and test data is done by taking the last 52 rows of the data in test and remaining in train. The usual 80-20% split is not done as we have time series data, so we need to consider the time frame in the data for the split, so a good chunk of time frame is tested as well. When we did the stationarity test the number of lags in the data is observed is 28. So, we took 52 data steps in test so we can cover maximum of the time lags in the data.