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Bed and Revenue Forecasting in Nursing Home Management System

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Abstract

Data management in nursing home typically stored in manual filing systems and hardcopy records. Despite the the adoption of digital systems has begun, the information gathered often remains underutilized, and fails to contribute to nursing home operations. Therefore, this study proposes the integration of predictive analytics to analyse and predict the need for bed capacity and revenue projections to determine the sustainability of nursing homes. This study utilized historical data of bed occupancy and revenue to train two forecasting models, ARIMA and Prophet, which are compared and evaluated based on metrics such as r2_score, mean squared error, and mean absolute error. The results show that the Prophet algorithm outperforms ARIMA in both bed and revenue forecasting. The system is implemented with a user-friendly web interface that allows users to input the date range for forecast and retrieves the forecast result from the backend. The proposed system provides nursing home managers with valuable insights into the future trends of bed occupancy and revenue, enabling them to make informed decisions and better manage their resources.

1. Introduction

Nowadays, the global trend of population aging is accelerating, and there is a growing demand for effective nursing home management systems. By utilizing modern technology and data-driven strategies, the system plays a crucial role in ensuring optimal resource allocation and enhancing the quality of care delivered in nursing homes. In the last sixty years, the proportion of adults aged 65 and older has shown a modest increase from 8% to 10% across many nations [1]. However, projections indicate a substantial escalation in this demographic over the next forty years, with estimates suggesting that it will surge from 800 million to 2 billion individuals, comprising 22% of the total population [1].

The elderly frequently live alone or in nursing institutions, either temporarily or permanently due to low population density and the migration of young people to wealthier areas. These nursing homes are updating their spaces to give their seniors greater services and attention, resulting in the expense of nursing homes and the standard of living for the elderly are impacted by these advancements [2]. The elderly often require assistance with their daily basic needs and may also suffer from various diseases requiring medication support or specialized treatment to sustain their well-being. Consequently, it is considered unsafe for seniors to live alone at home. Moreover, if a vulnerable adult is left unattended at home, the situation can escalate into a crisis before anyone becomes aware of it [3]. Besides, with the rising standards of living, an increasing number of families have both spouses working to sustain their livelihoods, leaving them with limited additional resources to care for elderly relatives. One out of three senior citizens in Malaysia do not receive financial support from their child or have been abandoned [4]. Consequently, nursing home emerge as one of the options that is suitable for the elderly who require assistance on a daily basis.

As the population of patients in nursing homes continues to increase, the volume of transactions and bed requirements also rise proportionally. Consequently, nursing homes must adopt a strategic approach to address the occupancy rate and bed availability challenges effectively. Additionally, effective cost management is crucial for sustainable business operations. With the growth in patient numbers, there is a corresponding need to hire more nurses and manage financial resources efficiently. Thus, prudent cost management is essential to mitigate the risk of financial issues and allows ample time to prepare and implement appropriate countermeasures if needed.

Therefore, this study aims to integrate predictive analytics in nursing home management system that addresses the increasing demand for beds and enhances cost management practices. By implementing predictive analytics models and strategic planning techniques, the project seeks to optimize bed allocation, ensure efficient resource utilization, and minimize financial risks.

2. Literatur Review

2.1 Predictive Analytics

As data becomes increasingly abundant in today's society, simply storing it in a database management system (DBMS) is no longer enough. Without taking any action on the data, its potential value remains untapped. Therefore, we propose the implementation of predictive analytics to extract insights and make predictions from the stored data, enabling organizations to make data-driven decisions and gain a competitive advantage in their respective industries.

Predictive analytics is a powerful tool that leverages big data to make forecasts about future events by using statistical knowledge based on past occurrences [5]. It is a branch of advanced analytics which uses a combination of statistical modelling, data mining techniques, and machine learning to create predictions for future outcomes or performance based on the historical data given by the user. Companies frequently employ predictive analytics to forecast future outcomes and discover growth patterns in data in order to identify risks and opportunities. In healthcare, predictive analytics allow for individualized clinical management decisions and patient counselling, as they take into account specific patient characteristics rather than relying on population averages [6].

2.2 Time-Series Forecasting Algorithm

Time-series forecasting algorithms are designed to analyse and predict future values based on historical patterns and trends within a time-dependent dataset. Some examples of popular time-series forecasting algorithms include ARIMA (Autoregressive Integrated Moving Average) and Prophet.

ARIMA is a model used for time series analysis and forecasting future values based on observed patterns [7]. If a statistical model forecasts future values using data from the past, it is said to be autoregressive [8]. ARIMA has been widely used in different domain such as healthcare, transportation and agriculture. Sahai et al. [9] use ARIMA to predict the spread of the COVID-19 epidemic in the US, Brazil, India, Russia and Spain. In a similar study, Tyagi et al. [10] uses an ARIMA model to predict the confirmed and active COVID-19 cases until mid-July, and also estimate the number of isolation beds, ICU beds, and ventilators needed to cater to the increasing number of COVID-19 patients.

Nath et al. [11] employed the ARIMA model to predict wheat production, while Jadhav et al. [12] assessed the accuracy of price forecasts for cereals using the ARIMA model. The results demonstrated the remarkable performance of the ARIMA model in predicting prices, as evidenced by its ability to generate precise price forecasts for the year 2020 [12]. On the other hand, Alghamdi et al. [13] address the growing issue of traffic congestion by using ARIMA-based modelling to examine the factors that contribute to it.

Another time series forecasting algorithm is Prophet. Facebook's Core Data Science team developed the Prophet model, a user-friendly time series forecasting tool that aims to provide accurate forecasts [14]. Prophet considers time series data to be a combination of different patterns, including trends, seasonality, and holidays [15]. Although Prophet has only been available for three years, it has gained a reputation for being a powerful model that is also user-friendly [16].

The prophet model can handle historical outliers by matching them with trend changes and forecasting similar changes in the future [8]. However, the best way to deal with outliers is to remove them. The model has no difficulty in handling missing data. Sardar et al. [8] and Aditya Satrio et al. [16] utilised both Prophet and ARIMA for forecasting the trend of COVID-19. From their study, the ARIMA model performs better for predicting confirmed cases in Afghanistan, Bangladesh, India, Maldives, and Sri Lanka, while the Prophet time series model is more suitable for forecasting cases in Bhutan and Indonesia. Although Prophet tends to deviate from the actual data the further it forecasts, the overall outcome demonstrates that it outperforms ARIMA [16].

3. Methodology

3.1 Initial Idea

Fig. 1 presents the flowchart for the bed and revenue forecasting. Users are required to enter a date range to the system, and the system will pass the date range to the backend PHP through Ajax and called the Python to load the model and produce the forecast result then send back to the frontend and generate the result into a graph and present it to the users.

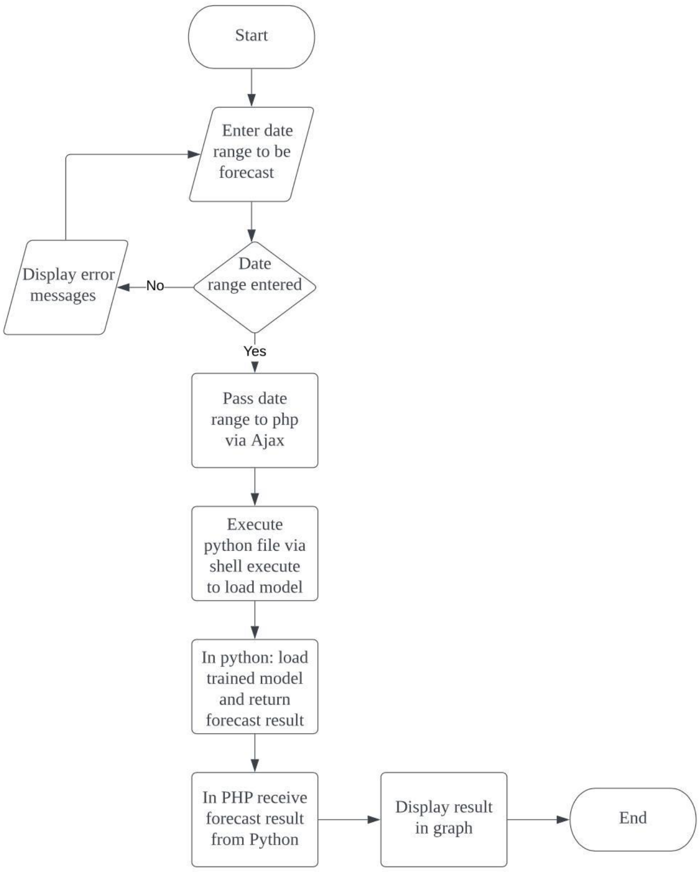

Fig. 1 *Flowchart for bed and revenue forecasting*

3.2 Dataset

In this stage, dataset will be collected for the preparation of model training. Since two forecast models are involved in the system, so total of two datasets will be collected. Bed dataset was obtained from the National Health Services in England [18]. The data that will be used for model training is the year and the number of beds occupied. Fig. 2 shows the overview of the bed dataset.

Due to the unprecedented COVID-19 pandemic that occurred between 2020 and 2021, the data from this period will be excluded from the dataset used in this study. This decision was made to ensure that the analysis accurately reflects typical conditions in nursing homes, unaffected by the exceptional circumstances of the pandemic. By removing this period from the dataset, the study aims to provide a more accurate representation of the factors affecting bed occupancy and costs in nursing homes, enabling more effective decision-making in these critical areas.

For the dataset of the revenue forecast model, a sample sales dataset is obtained from the internet to be used to train the revenue forecast model. Sales for each month starting from October 2009 to September 2015 have been recorded in the dataset. Before entering the model training phase, the obtained dataset must be processed to ensure there is no empty row available in the dataset and the data type is prepared for model training. Fig. 3 shows the overview of revenue dataset.

The bed dataset was segmented into quarters, providing a quarterly breakdown of occupancy rates. In contrast, the revenue dataset was organized on a monthly basis, capturing the financial performance month by month. This difference in granularity allows for a comprehensive analysis of both the occupancy trends and revenue patterns, considering the distinct time intervals for each dataset.

			Available					Occupied				
Year	Period	Org Name	Total	General & Acute	Learning Disabilities	Maternity	Mental Illness	Total	General & Acute	Learning Disabilities	Maternity	Mental Illness
2010/11	Q1	England	144,455	110,568	2,465	7,906	23,515	122,551	95,430	1,895	4,756	20,470
2010/11	Q2	England	141,477	108,349	2,237	7,962	22,929	119,298	92,775	1,766	4,879	19,878
2010/11	Q3	England	141,630	108,023	2,088	7,778	23,740	121,497	94,741	1,618	4,738	20,400
2010/11	Q4	England	142,319	108,890	1,974	7,848	23,607	123,279	96,566	1,519	4,738	20,456
2011/12	Q1	England	137,354	104,574	1,721	7,805	23,253	116,452	90,317	1,341	4,616	20,178
2011/12	Q2	England	138,525	105,545	1,784	7,987	23,208	116,372	89,981	1,412	4,841	20,139
2011/12	Q3	England	137,963	105,245	1,756	7,946	23,016	117,708	91,448	1,340	4,841	20,079
2011/12	Q4	England	140,454	107,449	1,937	7,948	23,121	122,105	95,633	1,450	4,851	20,171
2012/13	Q1	England	137,287	104,888	1,966	7,883	22,550	118,064	92,145	1,457	4,730	19,732
2012/13	Q2	England	135,559	103,730	1,743	7,816	22,269	115,730	89,917	1,414	4,736	19,663
2012/13	Q3	England	136,044	103,956	1,728	7,864	22,496	116,974	91,347	1,385	4,631	19,610
2012/13	Q4	England	138,178	106,374	1,697	7,839	22,268	121,108	95,516	1,378	4,486	19,728
2013/14	Q1	England	136,459	104,855	1,706	7,789	22,109	118,056	92,750	1,355	4,424	19,527
2013/14	Q2	England	135,037	103,643	1,662	7,707	22,025	115,146	89,614	1,357	4,522	19,653
2013/14	Q3	England	135,489	104,244	1,636	7,679	21,931	116,488	91,353	1,308	4,514	19,313
2013/14	Q4	England	136,811	105,581	1,671	7,829	21,731	119,663	94,571	1,296	4,549	19,246
2014/15	Q1	England	135,754	104,738	1,552	7,714	21,750	117,510	92,315	1,232	4,425	19,539
2014/15	Q2	England	134,753	103,758	1,518	7,858	21,618	116,300	90,948	1,244	4,732	19,376
2014/15	Q3	England	134,573	103,865	1,484	7,777	21,446	117,827	92,905	1,184	4,561	19,177
2014/15	Q4	England	136,946	106,250	1,455	7,868	21,374	121,202	96,343	1,157	4,571	19,130
2015/16	Q1	England	131,812	104,096	1,322	7,825	18,569	114,509	92,007	1,058	4,746	16,697
2015/16	Q2	England	130,619	102,271	1,302	7,797	19,249	112,010	89,036	1,027	4,795	17,151
2015/16	Q3	England	130,298	101,974	1,305	7,746	19,273	113,668	90,857	975	4,751	17,085
2015/16	Q4	England	131,561	103,422	1,306	7,746	19,086	117,125	94,364	942	4,725	17,094

Fig. 2 *Overview of bed dataset*

1	date	sales
2	1/10/2009	338630
3	1/11/2009	339386
4	1/12/2009	400264
5	1/1/2010	314640
6	1/2/2010	311022
7	1/3/2010	360819
8	1/4/2010	356460
9	1/5/2010	365713
10	1/6/2010	358675
11	1/7/2010	362027
12	1/8/2010	362682
13	1/9/2010	346069
14	1/10/2010	355212
15	1/11/2010	365809
16	1/12/2010	426654
17	1/1/2011	335608
18	1/2/2011	337352
19	1/3/2011	387092
20	1/4/2011	380754
21	1/5/2011	391970
22	1/6/2011	388636
23	1/7/2011	384600
24	1/8/2011	394548
25	1/9/2011	374895
26	1/10/2011	379364
27	1/11/2011	391081
28	1/12/2011	451669
29	1/1/2012	355058
30	1/2/2012	372523
31	1/3/2012	414275
32	1/4/2012	393035
33	1/5/2012	418648
34	1/6/2012	400996
35	1/7/2012	396020

Fig. 3 *Overview of revenue dataset*

3.3 Data Processing

Before model training stage, the dataset undergoes preprocessing procedures to ensure data integrity and appropriate formatting. Essential libraries such as pandas and numpy are imported for data manipulation tasks. The bed dataset is imported and inspected using df.info() to assess its completeness and identify any data type inconsistencies. While no null values are detected, the 'total' column is flagged as having an object datatype rather than integer, necessitating further preprocessing steps (see Fig. 4).

```
In [1]: import pandas as pd
        import numpy as np

In [2]: ##arima test
        df = pd.read_csv('C:/Users/Isaac/Desktop/bed_dataset.csv',index_col='year', parse_dates=True)

In [3]: from pandas.plotting import autocorrelation_plot
        df.info()

        <class 'pandas.core.frame.DataFrame'>
        DatetimeIndex: 42 entries, 2010-03-01 to 2022-03-01
        Data columns (total 1 columns):
         #   Column  Non-Null Count  Dtype
        ---  ------  --------------  -----
         0   total   42 non-null     object
        dtypes: object(1)
        memory usage: 672.0+ bytes
```

Fig. 4 *Inspect the dataset using df.info()*

Subsequently, the initial rows of the dataset are examined using df.head() to gain insight into its structure. It is observed that the 'total' column contains numerical values formatted with comma separators, indicating the need for preprocessing to convert these figures into integers (see Fig. 5).

```
In [5]: df.head()
Out[5]:
```

year	total
2010-03-01	122,551
2010-06-01	119,298
2010-09-01	121,497
2010-12-01	123,279
2011-03-01	116,452

Fig. 5 *Display first 5 rows of the bed dataset*

The preprocessing procedure involves utilizing the replace() function to remove comma separators from the 'total' column and subsequently converting it into an integer datatype (see Fig. 6). A similar preprocessing approach is applied to the revenue dataset, where pd.read_csv is utilized to import the dataset and df.info() is employed to confirm the absence of null values. Additionally, adjustments are made to the date format to ensure proper parsing of dates using the dayfirst parameter.

```
In [9]: df = df.replace(',','', regex=True)
        df['total']=df['total'].astype(int)
        df.info()

        <class 'pandas.core.frame.DataFrame'>
        DatetimeIndex: 42 entries, 2010-03-01 to 2022-03-01
        Data columns (total 1 columns):
         #   Column  Non-Null Count  Dtype
        ---  ------  --------------  -----
         0   total   42 non-null     int32
        dtypes: int32(1)
        memory usage: 504.0 bytes
```

Fig. 6 *Apply preprocessing technique to remove comma separator*

3.4 Model Training

In the model training phase, two algorithms, Prophet and ARIMA will be used to make comparisons in terms of accuracy for the forecast model.

3.4.1 ARIMA algorithm

The ARIMA model requires three parameters: 'p', 'd', and 'q', where 'p' represents the number of autoregressive terms, 'd' signifies the number of nonseasonal differences necessary for stationarity, and 'q' indicates the number of lagged forecast errors in the prediction equation. To determine the value of 'p', an autocorrelation plot is utilized, where the intercept value of the x-axis to the grey line corresponds to 'p', typically set as 5 (see Fig. 7).

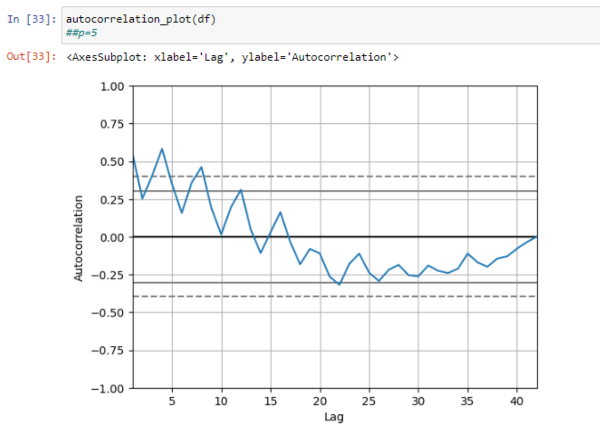

Fig. 7 *Autocorrelation plot for bed dataset*

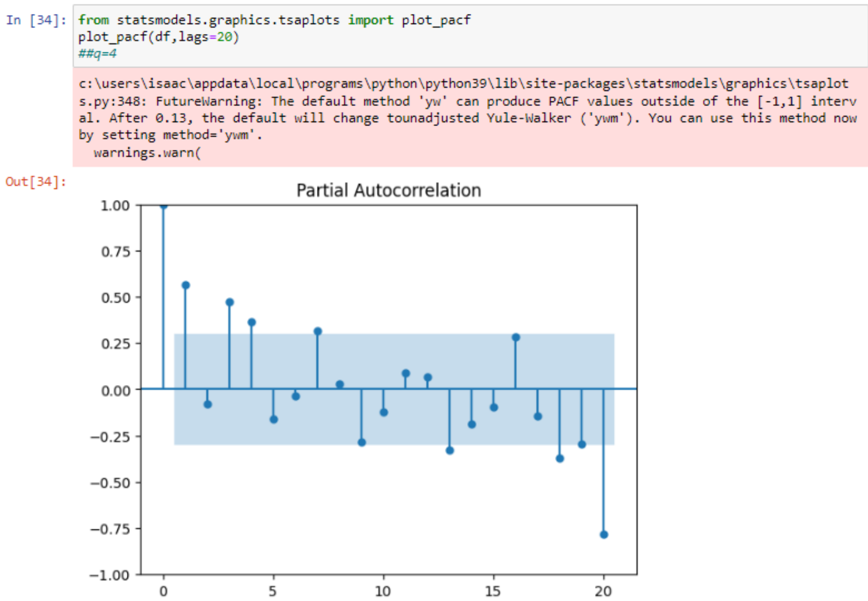

Fig. 8 *Partial auto correlation graph for bed dataset*

The value of parameter 'q' in the ARIMA model can be determined by examining the partial autocorrelation function plot (plot_pacf). The lag beyond which the partial autocorrelation is statistically significant (higher than the grey area) indicates the appropriate value of 'q', typically set as 4 in this case (see Fig. 8). The parameter 'd' is commonly set to 0 to denote no differencing.

Similar steps were conducted for the revenue dataset. The output of the autocorrelation_plot revealed a 'p' parameter value of 9, the 'q' parameter was determined to be 6, mirroring the procedure followed for the bed forecast model. The 'd' value remained unchanged at 0 for both datasets.

Once the parameters 'p', 'd', and 'q' are determined, the ARIMA model training process can be conducted. The dataset is split into training and testing sets, with the last 15 rows reserved for testing purposes. Subsequently, the ARIMA model is constructed using the training dataset and the identified parameters.

3.4.2 Prophet algorithm

```
In [119]: ##prophet test
          bed_df = df.reset_index()

In [120]: df=bed_df.rename(columns={'year':'ds', 'total':'y'})

In [121]: from prophet import Prophet
          import matplotlib.pyplot as plt
```

Fig. 9 *Preparation of dataset for model training*

Fig. 9 shows the initial preparation steps for implementing the Prophet algorithm. Firstly, the dataset index is reset to designate the date as the index. Subsequently, the column named 'year' is renamed as 'ds', and the column named 'total' is renamed as 'y', adhering to Prophet's specific requirements. Following these preparatory steps, the model training process can be started.

```
In [73]: model = Prophet(yearly_seasonality =False)
         model.fit(df);
         df.tail()

         21:17:49 - cmdstanpy - INFO - Chain [1] start processing
         21:17:49 - cmdstanpy - INFO - Chain [1] done processing

Out[73]:
```

	ds	y
37	2019-06-01	111938
38	2019-09-01	114757
39	2019-12-01	111321
40	2021-12-01	111871
41	2022-03-01	113651

Fig. 10 *Model training using Prophet*

Fig. 10 illustrates the model training process using the Prophet algorithm. The parameter 'yearly_seasonality' is set to false to prevent the prediction from being influenced by yearly patterns in the dataset, thereby avoiding the possibility of negative forecast outputs. These steps are similar for both datasets.

3.5 Model Evaluation

Following the model training phase, an evaluation will be conducted to compare the performance of the two algorithms on the dataset. Table 1. presents a comparison of key performance metrics for the two algorithms used in bed number prediction, ARIMA and Prophet.

Table 1 ***Comparison between ARIMA and Prophet for bed prediction mode***

	ARIMA	Prophet
R2 score	-3.01	0.59
Mean Squared Error	13670951	4367937
Mean Absolute Error	3171	1764

Based on the comparison of key performance metrics in the table, it can be observed that the Prophet algorithm has demonstrated superior performance, with a higher r2_score, and lower mean squared error and mean absolute error compared to the ARIMA model. Therefore, the Prophet algorithm has been selected as the optimal forecasting model for bed occupancy in nursing homes.

Similarly, an evaluation of the revenue forecast model will be conducted by comparing the performance of the ARIMA and Prophet algorithms. Table 2. presents the evaluation results of the ARIMA and Prophet algorithm for the revenue forecast model. Given the higher r2_score, lower mean squared error, and mean absolute error achieved by the Prophet algorithm, it has been selected to be implemented for the revenue forecast model in the project.

Table 2 ***Comparison between ARIMA and Prophet for revenue prediction model***

	ARIMA	Prophet
R2 score	0.73	0.99
Mean Squared Error	182192915	19250404
Mean Absolute Error	11577	3357

In the model training phase, two algorithms, Prophet and ARIMA will be used to make comparison in terms of accuracy for the forecast model. Starting from the bed forecast model, start with import the ARIMA model.

4. Model Implementation

As the Prophet algorithm shows a higher r2_score, lower mean squared error, and mean absolute error compared to ARIMA, it is selected for implementation in the bed forecast and revenue forecast page.

4.1 Bed Forecast

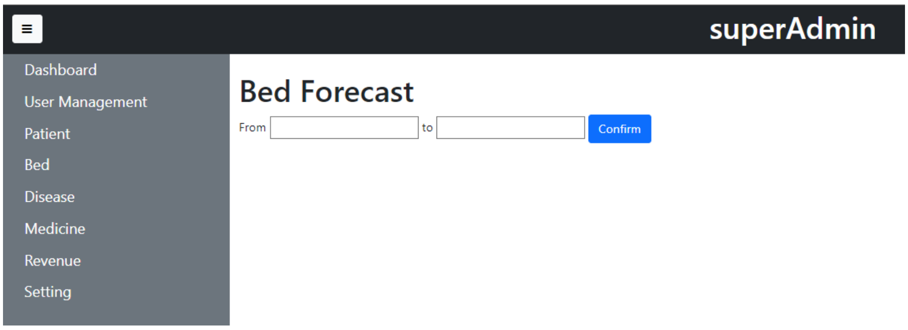

Fig. 11 *Bed Forecast page*

Fig. 11 shows the bed forecast page of the system. Users are required to enter the date range in future with a maximum of 6 months then click the 'Confirm' button and it will return the forecast result in graph form. The backend will execute a Python script to generate the bed forecast result based on the entered date range. The result will be returned to the frontend in JSON format after converting the date and forecast output. Fig. 12 shows the bed forecast result.

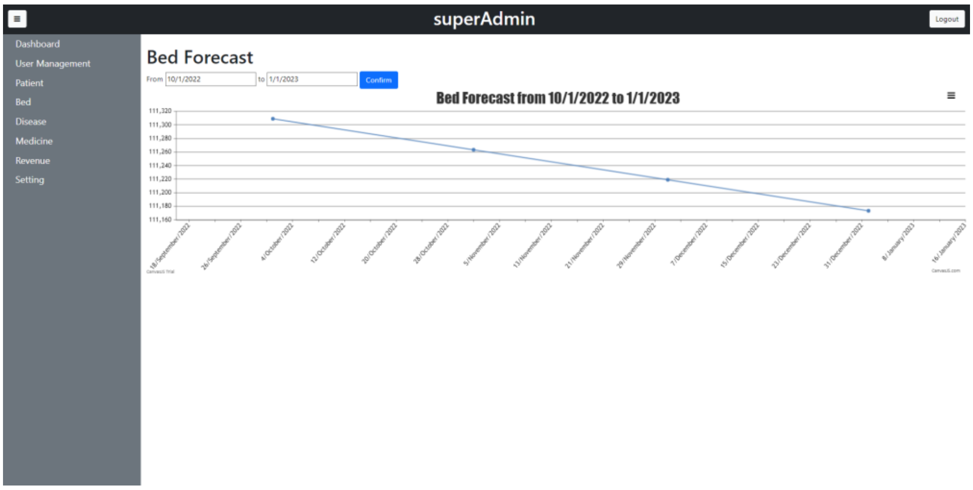

Fig. 12 *Bed forecast result page*

Fig. 13 shows the revenue forecast page of the system. Users are required to enter the date range in future with a maximum of 6 months then click the 'Confirm' button and it will return the forecast result in graph form. The process, which involves the execution of backend to frontend is similar to bed forecasting.

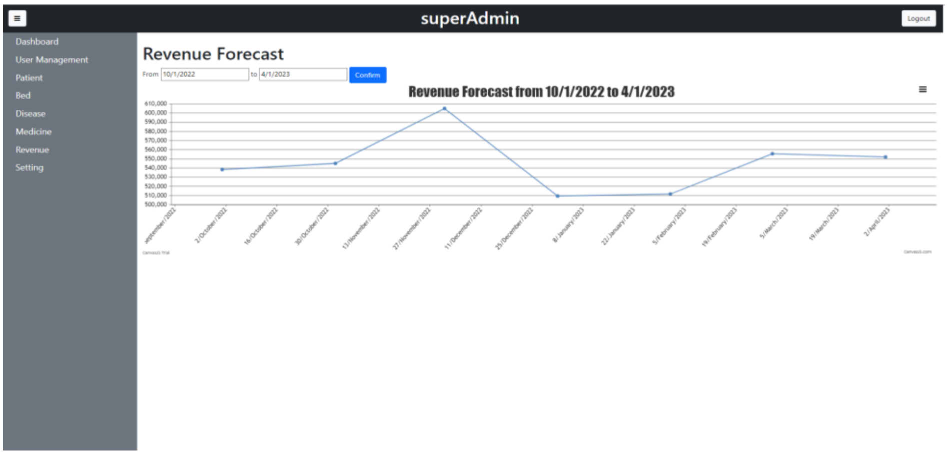

Fig. 13 *Revenue forecast result page*

The system developed in this study allows users to generate bed and revenue forecasts for a maximum of six months in the future. Future work could involve expanding the system to incorporate other forecasting methods and variables, as well as integrating it with other healthcare systems.

5. Conclusion

As the conclusion for this paper, the implementation of predictive analytics using the Prophet algorithm has shown promising results in forecasting bed occupancy and revenue for nursing homes. The use of this technology can help nursing homes in managing their costs more efficiently and providing better care for their patients. With further development and improvement, predictive analytics can be implemented in other areas of the healthcare industry to improve decision-making and overall efficiency.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Isaac, Fakhitah;* ***data collection:*** *Isaac;* ***analysis and interpretation of results:*** *Isaac;* ***draft manuscript preparation:*** *Isaac, Fakhitah. All authors reviewed the results and approved the final version of the manuscript.*

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