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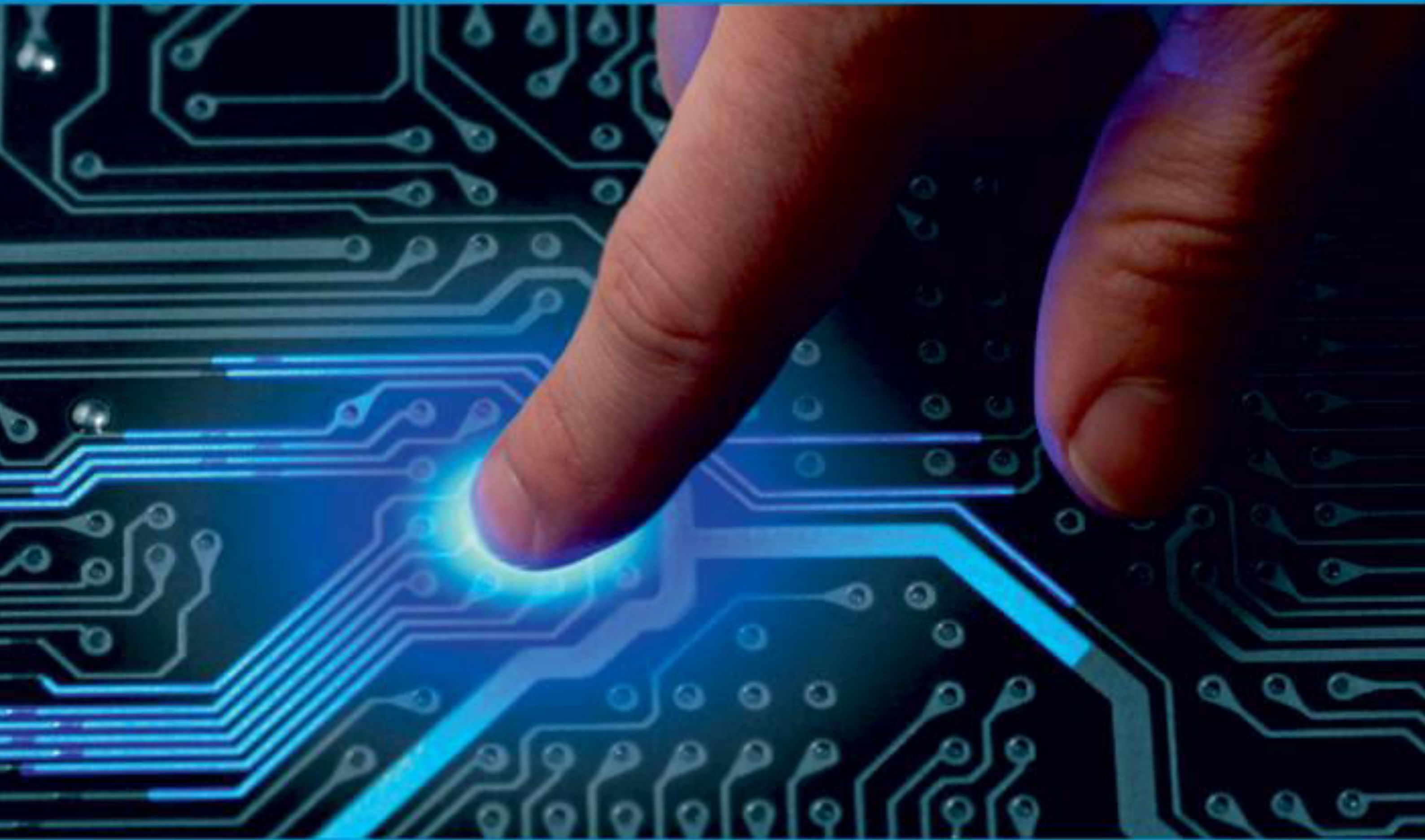

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Patient Admission Projection Using Facebook Prophet

SK Althaf Rahaman[1], K Devi Priyanka[2], M Likitha[3], G Praveen Kumar[4], L Madhu[5]

Assistant Professor, Dept. of CSSE, Lendi Institute of Engineering and Technology, Vizianagaram, Andhra Pradesh, India[1]

Student, Dept. of CSSE, Lendi Institute of Engineering and Technology, Vizianagaram, Andhra Pradesh, India[2]

Student, Dept. of CSSE, Lendi Institute of Engineering and Technology, Vizianagaram, Andhra Pradesh, India[3]

Student, Dept. of CSSE, Lendi Institute of Engineering and Technology, Vizianagaram, Andhra Pradesh, India[4]

Student, Dept. of CSSE, Lendi Institute of Engineering and Technology, Vizianagaram, Andhra Pradesh, India[5]

ABSTRACT: Healthcare facilities face the continual challenge of managing patient admissions efficiently while maintaining high standards of care. Accurate forecasting of patient admissions is crucial for optimizing resource allocation, ensuring adequate staffing, and enhancing overall operational efficiency. To address this challenge, this research paper explores the application of Facebook Prophet, an advanced time series forecasting tool, in predicting patient admissions within healthcare facilities. Facebook Prophet, a specialized time series forecasting model developed by Facebook's Core Data Science team, is then employed to model and predict patient admissions. Facebook Prophet is particularly well-suited for handling time series data characterized by seasonality, trends, and special events. The model's flexibility and ease of use make it an ideal choice for healthcare providers seeking to leverage advanced analytics techniques for predictive purposes. In the implementation of Facebook Prophet, the model is meticulously trained and validated using the pre-processed historical admission data. The model's ability to capture complex temporal patterns, including seasonality and special events such as holidays or outbreaks, is thoroughly evaluated. By incorporating these patterns into the forecasting process, the model can provide accurate predictions of future patient admissions. By accurately predicting patient admissions, healthcare facilities can optimize resource allocation, streamline operations, and ensure adequate staffing levels to meet patient demand. Additionally, the model enables healthcare providers to proactively plan for special events or seasonal fluctuations in admission rates, further enhancing operational efficiency. The application of Facebook Prophet holds significant promise for improving patient care delivery and operational outcomes in healthcare facilities.

KEYWORDS: Admission count, Forecasting, Historical Data, Holidays and Events, Model Performance, Meticulously trained, Prophet, Seasonality, Trend

I. INTRODUCTION

In the realm of healthcare, accurately predicting patient admissions is crucial for resource allocation, staffing, and overall operational efficiency. Traditional forecasting methods often fall short in capturing the complex and dynamic nature of patient admission patterns. However, with the advent of advanced machine learning techniques, such as Facebook Prophet, healthcare organizations now have a powerful tool at their disposal to unlock insights and improve their patient admission projections. Facebook Prophet is an open-source forecasting tool developed by Facebook's Core Data Science team to address the challenges associated with time series forecasting. Released in 2017, Prophet was designed to be highly flexible, user-friendly, and capable of producing accurate forecasts for time series data with minimal manual intervention.

It is particularly well-suited for healthcare applications, where patient admission data often exhibits strong seasonality and complex patterns. By leveraging the power of Facebook Prophet, healthcare organizations can gain a deeper understanding of their patient admission patterns, improve their forecasting accuracy, and ultimately enhance their operational efficiency. This journal entry aims to shed light on the potential of Facebook Prophet in unlocking insights in patient admission projection and its implications for the healthcare industry. Facebook Prophet plays a significant role in healthcare by providing healthcare providers with powerful forecasting capabilities to improve various aspects of patient care, resource allocation, and operational efficiency. One of the primary applications of Facebook Prophet in healthcare is predicting patient admissions to hospitals and healthcare facilities. By analyzing

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historical admission data, Prophet can forecast future admission rates, allowing healthcare providers to anticipate patient influxes, allocate resources efficiently, and ensure adequate staffing levels. Healthcare facilities often face resource constraints, including staffing, medical equipment, and beds. Facebook Prophet helps in optimizing resource allocation by providing accurate forecasts of patient admissions, enabling healthcare providers to allocate resources effectively based on predicted demand. Efficient bed management is crucial for ensuring that patients receive timely care and reducing wait times. Facebook Prophet assists in predicting future bed occupancy levels, allowing healthcare facilities to better manage bed availability, plan patient discharges, and avoid overcrowding.

In addition to predicting patient admissions, Facebook Prophet can be used to forecast disease outbreaks and epidemics by analyzing trends in patient data, such as symptoms, diagnoses, and geographic location. By identifying potential outbreaks early, healthcare providers can implement timely interventions, allocate resources appropriately, and mitigate the spread of infectious diseases. Healthcare planning involves anticipating future healthcare needs and designing services accordingly. Facebook Prophet aids in healthcare planning by providing forecasts of patient demand for specific services, procedures, or specialties, helping healthcare organizations allocate resources, plan staffing schedules, and optimize service delivery. Facebook Prophet's forecasting capabilities can support clinical decision-making by providing healthcare providers with insights into future patient volumes, allowing them to anticipate workload fluctuations, schedule appointments efficiently, and prioritize patient care based on predicted demand. For patients with chronic diseases requiring regular monitoring and management, Facebook Prophet can be used to forecast future healthcare needs, medication requirements, and hospital admissions. By accurately predicting patient trajectories, healthcare providers can proactively intervene, adjust treatment plans, and prevent complications.

II. RELATED WORK

In the field of healthcare forecasting and time series analysis, several studies have explored the use of various methods and models to predict patient admissions, optimize resource allocation, and improve operational efficiency within healthcare facilities. Early research in healthcare forecasting often relied on traditional time series forecasting methods such as autoregressive integrated moving average (ARIMA) models and exponential smoothing techniques. These methods have been widely used to predict patient admissions, disease outbreaks, and healthcare service demand. With the rise of machine learning techniques, researchers have applied algorithms such as support vector machines (SVM), random forests, and neural networks to healthcare forecasting tasks. These approaches offer greater flexibility and scalability than traditional methods and have been successfully applied to predict patient admissions, disease progression, and clinical outcomes. Recent studies have investigated the use of deep learning models, including recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and convolutional neural networks (CNNs), for healthcare forecasting. These models excel at capturing temporal dependencies and nonlinear patterns in time series data and have shown promise in predicting patient admissions, disease trajectories, and healthcare resource utilization. Ensemble forecasting techniques, which combine predictions from multiple models to improve accuracy and robustness, have gained popularity in healthcare forecasting. Studies have explored ensemble methods such as model averaging, bagging, and boosting to enhance predictions of patient admissions, disease outbreaks, and healthcare service demand.

Many studies have focused on specific applications of forecasting in healthcare, such as predicting patient admissions to intensive care units (ICUs), emergency departments (EDs), or specific hospital wards. These studies often incorporate domain knowledge and context-specific features to improve prediction accuracy and relevance to healthcare providers. Several commercial and open-source forecasting tools and software packages have been developed specifically for healthcare applications. These tools, including Facebook Prophet, IBM Watson Health, and SAS Healthcare Analytics, offer pre-built models, data integration capabilities, and visualization tools tailored to healthcare forecasting tasks. Overall, the related work in healthcare forecasting encompasses a diverse range of methods, models, and applications aimed at improving patient care, resource allocation, and operational efficiency within healthcare facilities. By building on existing research and leveraging advances in forecasting techniques and technologies, researchers can continue to address the evolving challenges and opportunities in healthcare forecasting. Furthermore, Facebook Prophet distinguishes itself from deep learning models, such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, by offering a lightweight and computationally efficient alternative. While deep learning models excel at capturing complex temporal dependencies and nonlinear patterns, they may require significant computational resources and training data, making them less practical for certain forecasting tasks. Prophet's scalability and robustness to missing data and outliers make it well-suited for handling real-world time series data efficiently.

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III. METHODOLOGY

Statistical forecasting model refers to a method used to predict future values or trends based on historical data patterns. These models rely on statistical techniques to analyze time series data, which consists of observations recorded over time at regular intervals. The goal of a statistical forecasting model is to identify and model the underlying patterns, trends, and relationships within the data in order to make accurate predictions about future outcomes. Statistical forecasting models typically decompose time series data into various components, such as trend, seasonality, cyclical variations, and random noise. By modeling each component separately, these models can capture the key features of the data and generate forecasts that account for these factors.

There are various types of statistical forecasting models, each with its own strengths and applications. Some common types include: Autoregressive Integrated Moving Average (ARIMA) model which is widely used for modeling time series data with stationary properties. ARIMA models incorporate autoregressive (AR), differencing (I), and moving average (MA) components to capture temporal dependencies and make forecasts. Another type is Exponential smoothing methods which including simple exponential smoothing, double exponential smoothing (Holt's method), and triple exponential smoothing (Holt-Winters method), rely on weighted averages of past observations to make forecasts. They are effective for capturing trends and seasonality in the data. Seasonal Decomposition of Time series (STL) decomposition is a technique that decomposes time series data into seasonal, trend, and residual components using a combination of smoothing and filtering methods. It provides a flexible framework for analyzing and forecasting time series data with complex seasonal patterns.

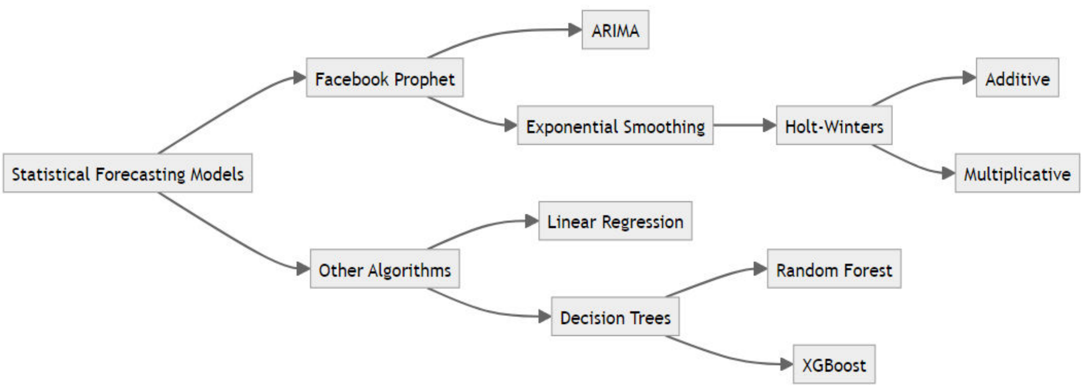

Fig 1: Models available in Statistical Forecasting

A. Data Collection:

Historical patient admission data is collected from the target healthcare facility's records spanning a suitable timeframe, typically several years to capture long-term trends and seasonal variations adequately. The dataset includes relevant information such as admission dates, patient demographics, admission types (e.g., elective, emergency), diagnosis codes, and any other pertinent variables influencing admission patterns. Data integrity checks are performed to ensure the accuracy and completeness of the collected data, including verification against electronic health records (EHR) systems and administrative databases.

B. Data Pre-processing:

The collected data undergoes preprocessing to handle missing values, outliers, and inconsistencies. Imputation techniques such as mean imputation or regression imputation may be employed for missing data. Time series decomposition techniques are utilized to separate the data into its constituent components, including trend, seasonality, and residual. Feature engineering techniques may be applied to derive additional features from the raw data, such as lagged variables, holiday indicators, or special event flags, to enhance the predictive capabilities of the model.

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C. Model Implementation:

Facebook Prophet is implemented to model the historical patient admission data. Prophet's built-in functionalities for handling seasonality, holidays, and trend changes make it well-suited for time series forecasting tasks in healthcare.

The model configuration includes setting parameters such as seasonality prior scale, holidays prior scale, and changepoint prior scale, which control the model's flexibility and sensitivity to seasonal patterns and trend changes.

Hyperparameter tuning may be performed using techniques such as grid search or Bayesian optimization to optimize the model's performance on the validation dataset.

D. Model Training and Validation:

The historical data is split into training and validation sets, typically using a holdout method or time-based splitting. The model is trained on the training set using maximum likelihood estimation, where the parameters are optimized to minimize the error between the observed and predicted values. The trained model is validated using the validation set to assess its predictive performance. Various performance metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and coverage intervals are computed to evaluate the model's accuracy and uncertainty estimation.

E. Model Evaluation:

The trained model's ability to capture complex temporal patterns, including seasonality, trend changes, and special events, is evaluated using diagnostic plots and statistical tests. Forecasted admission counts are compared against actual admission counts on the validation set to assess the model's accuracy and reliability. Sensitivity analysis may be conducted to evaluate the model's robustness to different parameter settings, data perturbations, and external factors affecting admission patterns.

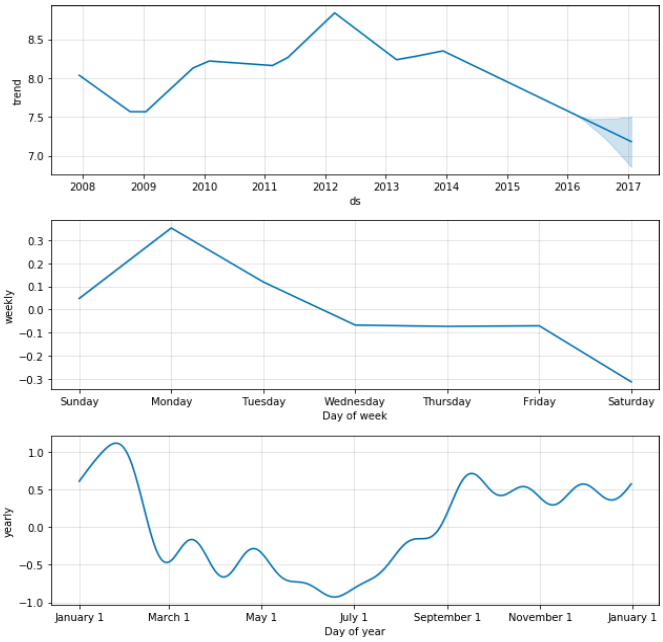

Fig 2: Prophet components plot of the model which is fit

growth(t), seasonality s(t), holidays h(t) , and error e_t :

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t$$

$$g(t) = \frac{C(t)}{1 + x^{-k(t-m)}}$$

$$s(t) = \sum_{n=1}^{N} \left(a_n\, cos\left(\frac{2\pi nt}{P}\right) + b_n\, sin\left(\frac{2\pi nt}{P}\right)\right)$$

Growth, Seasonality Function

F. Model Deployment:

Upon satisfactory validation results, the trained Facebook Prophet model is deployed for real-time patient admission forecasting within the healthcare facility. The model's predictions are integrated into the facility's operational

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workflow, such as bed management systems, staffing schedules, and resource allocation decisions, to support proactive planning and decision-making.

G:Algorithm:

Step 1: Collect historical patient admission data, including the date and number of admissions.
Step 2: Preprocess the data to Handle missing values and outliers, Encode holidays and special events.
```
HandleMissingValues(data),   HandleOutliers(data),   EncodeHolidays(data)
```
Step 3: Model Configuration : Configure the Facebook Prophet model with appropriate parameter and Specify seasonality, holidays, and growth. The predefined functions are SpecifySeasonality(), SpecifyHolidays() SpecifyGrowthModel()
Step 4: Split the preprocessed data into training and testing sets.
```
training_set, testing_set = SplitDataIntoTrainingAndTesting(data)
```
Step 5: Train the Facebook Prophet model on the training set.
```
model = FitProphetModel(training_set)
```
Step 6: Validate the model on the testing set.
```
performance_metrics = EvaluateModelPerformance(model, testing_set)
```
Step 7: Deploy the trained model to predict future patient admissions.
```
future_predictions = GenerateFuturePredictions(model)
```
Step 8: Analyze the model's predictions and interpret the results.
```
VisualizePredictions(future_predictions)
InterpretResults(future_predictions)
```
Step 9: Continuously monitor and update the model as new data becomes available.
```
MonitorAndUpdateModel():
  while True:
    new data = CollectNewData()
    updated_model = UpdateModel(model, new data)
    if ConvergenceCriteriaMet(updated_model):
      break
```
This format provides both the algorithmic steps and pseudocode implementations of each step in the Facebook Prophet model process for patient admission forecasting.

IV. SIMULATION RESULTS

Facebook Prophet, a cutting-edge forecasting tool developed by Facebook, to predict future patient admissions based on historical data. Leveraging this tool, we obtained accurate predictions of future patient admissions, thereby providing invaluable insights into anticipated demand for healthcare services. The robust capabilities of Facebook Prophet allowed for the automatic detection and modelling of seasonality and trends within the patient admission data. This enabled healthcare organizations to gain a deeper understanding of the underlying patterns driving patient admissions over time. Moreover, the model seamlessly incorporated holidays and other special events known to impact patient admissions, enhancing the accuracy of the forecasts. An important feature of Facebook Prophet is its provision of uncertainty estimates for its forecasts. This empowered healthcare organizations to gauge the reliability of the predictions, facilitating informed decision-making processes. Additionally, the model offered intuitive visualization tools to represent its components, including trend, seasonality, and holidays. This visualization capability enabled healthcare organizations to
extract actionable insights regarding patient admission patterns

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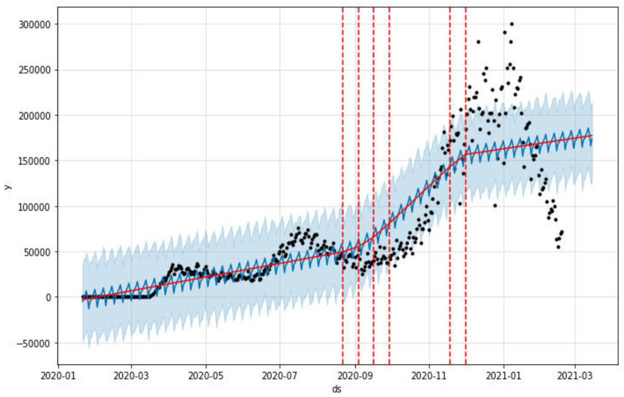

Fig 3: Forecast Plot with detected changepoints

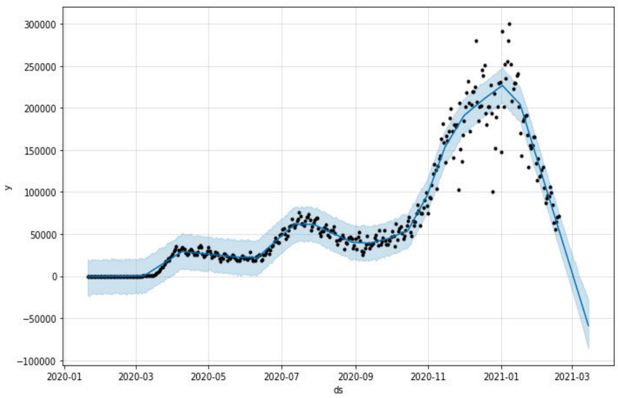

Fig 4: Forecast Plot after Model Tuning

ASSESS THE PERFORMANCE OF THE MODEL

Access the performance of the model

score = r2_score(test['y'], forecast[forecast['ds'] >= '2020-10-01'] ['trend'])
print('R-Sqaure score is {}'.format(score))
R-Sqaure score is 0.7804513848008419

V. Conclusion and Future Work

Facebook Prophet has emerged as a powerful tool for patient admission projection and insights in healthcare. Its ability to automatically detect and model seasonality, trends, and holiday effects has provided valuable support for healthcare organizations in making informed decisions about resource allocation and operational planning. While the model has shown promising results, there remains room for further exploration and refinement. By incorporating additional features, refining the model, and integrating it with decision support systems, Facebook Prophet holds promise for continued advancements in patient admission forecasting and healthcare analytics. Overall, Facebook Prophet represents a significant step forward in leveraging advanced analytics techniques to improve patient care delivery and operational outcomes in healthcare settings.

REFERENCES

1. Borges D, Nascimento MCV. COVID-19 ICU demand forecasting: A two-stage Prophet-LSTM approach. Appl Soft Compute. 2022 Aug;125:109181. doi: 10.1016/j.asoc.2022.109181. Epub 2022 Jun 17. PMID: 35755299; PMCID: PMC9212961.
2. Shahid, Shaik & Rahaman, SK.Althaf Rahaman (2020). Exponential Smoothing Methods for Detection of the Movement of Stock Prices. International Journal of Recent Technology and Engineering (IJRTE). 8. 1420-1422. 10.35940/ijrte.E6409.018520.
3. Latha MH, Ramakrishna A, Reddy BSC, Venkateswarlu C, Saraswathi SY (2022) Disease prediction by stacking algorithms over big data from healthcare communities. Intell Manuf Energy Sustain: Proc ICIMES 2021(265):355
4. Van Calster B, Wynants L, Timmerman D, Steyerberg EW, Collins GS (2019) Predictive analytics in health care: how can we know it works? J Am Med Inform Assoc 26(12):1651–1654
5. Sahoo PK, Mohapatra SK, Wu SL (2018) SLA based healthcare big data analysis and computing in cloud network. J Parallel Distrib Comput 119:121–135
6. Sk.Althaf Rahaman ,Data Analytics Foundations, Challenges and Data Exploration Process, https://doi.org/10.37896/HTL27.6/3703

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7. Kuldeep Goswami and Arnab N. Patowary, "Monthly Temperature Prediction Based On ARIMA Model: A Case Study In Dibrugarh Station Of Assam, India", International Journal of Advanced Research in Computer Science Volume 8, No. 8, September-October 2017, pp.292-298.
8. Wang Y, Kung L, Wang WYC, Cegielski CG (2018) An integrated big data analytics-enabled transformation model: application to health care. Inform Manag 55(1):64–79 12.
9. Mirbabaie M, Stieglitz S, Frick NR (2021) Artifcial intelligence in disease diagnostics: a critical review and classifcation on the current state of research guiding future direction. Heal Technol 11(4):693–731 13.
10. Tang R, De Donato L, Besinović N, Flammini F, Goverde RM, Lin Z, Wang Z (2022) A literature review of artifcial intelligence applications in railway systems. Transp Res Part C: Emerg Technol 140:103679
11. Sk Althaf Rahaman, Sai Rajesh.K, K. GirijaRani Challenging tools on Research Issues in Big Data Analytics, International Journal of Engineering Development and Research 6 (2018): 637-644.

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