**Integrating a Machine Learning Algorithm to Forecast Daily Asthma Hospitalizations**

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**Abstract**

**Purpose:** Acute asthma is one of the most frequent causes of hospital admissions in children. However, there is a lack of deep learning methods for decision making in clinical care for asthma patients. We sought a time series forecasting algorithm for future hospitalizations to improve preventive care to asthma patients.

**Methods:** Daily hospitalizations meeting the criteria for asthma exacerbations at Cincinnati Children’s Hospital were collected from the electronic health record, capturing roughly 95% of in-county admissions. Hospitalizations from Hamilton County, the City of Cincinnati, and one high morbidity neighborhood were collected from January 1, 2016, to June 30, 2023. We integrated and compared the performance of traditional forecasting algorithms to a Prophet machine learning algorithm trained on all but the last two years of hospitalizations. We collected qualitative feedback from clinical care providers to calibrate the algorithms.

**Results:** There were 588 days (21.5%) with no asthma hospitalizations, 761 days (27.8%) with one, 566 days (20.7%) with two, 408 days (14.9%) with three, and 413 days (15.1%) with four or more. The Prophet algorithm had better cross-validated prediction accuracy (Median Absolute Percentage Error (MAPE): 0.516) than the traditional forecasting algorithm (MAPE: 0.831). Calibration resulted in a 5% high-risk threshold (sensitivity: 0.771; specificity: 0.696; AUC: 0.805, 95% confidence interval: (0.776, 0.834)). The Prophet algorithm was superior to the traditional forecasting algorithm for timing and quantifying future asthma hospitalizations.

**Conclusions:** Integrating machine learning techniques with approaches to pediatric asthma care offers enhanced prediction of future exacerbations that could enable proactive prevention when integrated with clinical operations.

**Keywords:** asthma, forecasting, time series, pediatric hospitalizations

**List of Abbreviations**

AHLS – Asthma Health Learning System

ARIMA – autoregressive integrated moving average model

CCHMC – Cincinnati Children’

CNN – convolutional neural network

ETS – exponential smoothing (error, trend, seasonality) model

LSTM – long short-term memory model

MAPE – median absolute percentage error

1. **Introduction**

Acute asthma is one of the most frequent causes of hospital admissions, especially in children,1,2 with non-Hispanic Black children having the highest prevalence of hospitalizations for asthma exacerbations.3 Approximately 12 million people in the United States experience an acute asthma exacerbation each year, a quarter of which require hospitalization.4 Air exacerbations occur in the body’s airways, where air travels to and from the lungs.5 As air moves through the lungs, the airways become smaller. During an asthma exacerbation, the sides of the airways inside the lung swell and the airways shrink, reducing the amount of air that can travel to and from the lungs.6 Patients with acute asthma attacks exhibit increasing shortness of breath, chest tightness, coughing, and/or wheezing.7 Children with uncontrol asthma have a lower quality of life,8 and the total direct costs of pediatric asthma were US $5.92 billion in 2013.9 Asthma exacerbations are key to defining the severity of the disease and their prevention is an important metric to measure the success of various asthma treatments.10

There are challenges to improve outcomes related to asthma attacks and understanding the underlying complexity of triggers which have hindered efforts to mitigate the risk through targeting appropriate preventative treatment.11 Identifying children at risk of an asthma attack provides the opportunity to prevent these attacks and improve health outcomes.7 Various clinical symptoms and signs can assist the clinician in determining the severity of acute asthma, and the presence of major risk factors for near-fatal and fatal asthma makes early recognition and treatment of an asthma exacerbation essential.4 Caregivers have identified challenges associated with asthma care for children with a previous hospital admission as well as solutions to improve care and potentially reduce readmissions.11,12

The pediatric Asthma Learning Health System (ALHS) is a network organizational architecture launched in March 2022 at Cincinnati Children's Hospital Medical Center (CCHMC) in Cincinnati, Ohio, that enables clinical and community service providers, as well as families, to spur collective action, accelerate research, and improve health outcomes to children with asthma and asthma-related symptoms.13 Their activities include (1) a shared asthma dashboard and approach to population-level patter recognitions; (2) weekly multidisciplinary asthma meetings with the clinicians and caregivers to align the needs of researchers and caregivers, and (3) develop tools to enhance the social needs screenings and responses. AHLS was created to serve the youth living in Hamilton County, the population center for the City of Cincinnati and the surrounding areas. Approximately 190,000 children live in Hamilton County, of which it is estimated that 30,000 have asthma.

There is a lack of application of deep learning methods for decision making in clinical care for asthma patients, particularly those among traditionally underserved populations. The overall goal of this work was to develop, implement, calibrate, and optimize an asthma time series forecasting algorithm to predicts future asthma hospitalization admissions in Hamilton County, Ohio. Time series forecasting has always been a major topic in data science with a plethora of applications.14 Well-known traditional time series models such as an Autoregressive Integrated Moving Average (ARIMA) model which account for underlying trends and autocorrelated time series,15,16 and Exponential Smoothing (ETS) models17 that focus on error, trend, and seasonality, have been widely used for forecasting algorithms, whose applications include prediction of tuberculosis incidence rates in Taiwan,18 COVID-19 hospitalizations in Italy,19 and for forecasting water level changes for sustainable environmental management.20 These traditional forecasting methods are not always appropriate to study and forecast large and noisy time series data, generating particular interest in machine learning models like Long short-term memory (LSTM) networks21 and convolutional neural networks (CNNs).22 Recently, a forecasting tool developed by Facebook and based on a Generative Additive Model (GAM)23 called Prophet24 has been seen for its simplicity and scalability, making it specifically tailored for business forecasting problems and handles missing data extremely well.25 Comparisons between the traditional forecasting algorithms to machine learning algorithms largely depend upon the approach, the application of the model, the nature and complexity of the data, and scalability.14 An application of ARIMA, LSTM, and Prophet models on 65 wells in the DJ Basin, Colorado show that ARIMA and LSTM perform better than Prophet.26 On the other hand, seasonal ARIMA, LSTM, and Prophet models were used to predict total and peak monthly energy demand in India, where the investigators found that seasonal ARIMA and LSTM models had higher prediction errors than Prophet.27 Both studies found that Prophet was quick to setup and fine tune but was not as accurate as the well-established time series models which required pre-processing of the data, and that deep learning methods required much longer development times for hyperparameter tuning but had much better performance than either Prophet or traditional time series models.

We compared the performance of classical time series forecasting models ARIMA and ETS to a Prophet model on asthma hospitalization admissions of pediatric patients in Hamilton County, Ohio. Our goal was to develop a forecast model to predict future asthma admissions to increase the prevention of admittance among affected communities and to improve translational research in asthma for caregivers and healthcare providers, in accordance with the ALHS’s mission. We selected the best time series model for each class of ARIMA, ETS, and Prophet, and then evaluated the performance of the three best models based on prediction accuracy and timing of the predictions. We shared our results and incorporated feedback from healthcare professionals who provided input into our models to enhance performance. Through application in a real-world setting of pediatric asthma admissions, we hope to contribute to the discussion of machine learning in time series forecasting algorithms. The models developed herein will be a first step to assist departments with preparation abilities, make caregivers aware of the potential of increased hospitalizations, and to optimize staff and resources in health care to maximize care for youth with asthma.

1. **Methods**

We used electronic health record data to calculate asthma hospitalization rates of youth in the study region. Hospitalizations meeting the criteria for asthma were identified through the electronic health record in Hamilton County, Ohio, the City of Cincinnati, and the neighborhood of Avondale, a suburb of Cincinnati with a large minority population and a high percentage of poverty. Daily asthma hospitalizations were recorded from January 1, 2016, to June 30, 2023.

1. **Results**
2. **Discussion and Conclusions**

**Declarations**

*Ethics Approval*

We are exempt from NIH’s guidelines for Human Subjects (Section 46.104(d)(4) of the NIH 2018 Revised Common Rule Requirements). Our study does not involve contacting patients directly. We have used deidentified data not collected specifically for this study.

*Data Availability*

The authors do not have permission to share the data.

*Author Contributions*

Stephen Colegate – conceptualization, methodology, software, formal analysis, writing - original draft, writing - review & editing

Michael Seid – conceptualization, methodology, writing – original draft, writing – review & editing, funding acquisition

David Hartley – conceptualization, methodology, writing - original draft, writing – review & editing

Aaron Flicker – methodology, software, data curation, writing – review & editing

Joseph Bruce – conceptualization, methodology, software, data curation

Andy Beck – conceptualization, methodology, writing – original draft, writing – review & editing, funding acquisition

Cole Brokamp – conceptualization, methodology, writing - original draft, writing - review & editing, funding acquisition

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*Conflicts of Interest*

None declared.

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