Forecasting Seasonal Trends in Ear Nose Throat Diseases: A Comparative Analysis of Statistical and Machine Learning Models

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Abstract: This study examines patterns of seasonal illnesses at an ENT hospital using statistical methods and advanced machine learning techniques to improve disease prediction and support healthcare planning. The data underwent careful cleaning to ensure accuracy, which involved identifying outliers, managing missing values, and normalising information. The study looked at how seasonal illnesses develop, using a mix of techniques. This research used advanced tools like Long Short-Term Memory (LSTM) networks and Prophet, as well as simpler models such as Holt-Winters and SARIMA. To make the models easier to understand, there is an application of SHAP (SHapley Additive Explanations) values. Finally, the article used statistical measures and confidence intervals to assess forecast accuracy. Moreover, to discover how weather influences sickness seasonality, connections between patterns of disease incidence and environmental variables like temperature, humidity, and rainfall have been additionally looked at with the aid of the usage of correlation prediction. Overall, this method shows how conventional and system gaining knowledge of models can monitor seasonal illness traits. The effects do not only simplest display the disease patterns, but it also assists with allocating resources and making guidelines for better healthcare management.

Keywords: *seasonal disease forecasting, machine learning and statistical forecasting, environmental correlation in healthcare.*

Tiêu đề: **Dự báo xu hướng mùa vụ trong các bệnh tai mũi họng: Phân tích so sánh giữa các mô hình học máy thống kê**

Tóm tắt: Bài nghiên cứu này xem xét các mô hình bệnh theo mùa tại một Bệnh viện Tai Mũi Họng bằng cách sử dụng các phương pháp thống kê và kỹ thuật học máy tiên tiến để cải thiện dự đoán bệnh và hỗ trợ lập kế hoạch chăm sóc sức khỏe. Dữ liệu đã trải qua quá trình làm sạch cẩn thận để đảm bảo tính chính xác, bao gồm xác định các giá trị ngoại lệ, quản lý các giá trị bị thiếu và chuẩn hóa thông tin. Nghiên cứu này tập trung vào cách các bệnh theo mùa phát triển, sử dụng kết hợp các kỹ thuật khác nhau. Nghiên cứu này sử dụng các công cụ tiên tiến như mạng Long Short-Term Memory (LSTM) và Prophet, cũng như các mô hình đơn giản hơn như Holt-Winters và SARIMA. Để làm cho các mô hình dễ hiểu hơn, có một ứng dụng của các giá trị SHAP (SHapley Additive Explanations). Cuối cùng, bài báo đã sử dụng các biện pháp thống kê và khoảng tin cậy để đánh giá độ chính xác của dự báo. Hơn nữa, để khám phá cách thời tiết ảnh hưởng đến tính thời vụ của bệnh tật, các mối liên hệ giữa các mô hình mắc bệnh và các biến môi trường như nhiệt độ, độ ẩm và lượng mưa cũng đã được xem xét với sự hỗ trợ của dự đoán tương quan. Nhìn chung, phương pháp này cho thấy các mô hình học máy truyền thống và hệ thống có thể theo dõi các đặc điểm bệnh theo mùa. Các tác động không chỉ đơn thuần hiển thị các mô hình bệnh tật mà còn hỗ trợ phân bổ nguồn lực và đưa ra các hướng dẫn để quản lý chăm sóc sức khỏe tốt hơn.

Từ khóa: *dự báo bệnh theo mùa, dự báo và học máy thống kế, tương quan môi trường trong chăm sóc sức khỏe.*

I. INTRODUCTION

For many diseases, the seasonal timing profoundly impacts prognosis, treatment, and health care management. In-depth information about these seasonal processes is critical for effective healthcare architecture and the construction of useful products. This study examines the temporal evolution of the most frequently used ICD disease models in the Saigon ENT Hospital, revealing seasonal peaks in disease incidence and informing resource allocation decisions for continuous patient care. This study used detailed data (diagnostic cases) from the Saigon ENT Hospital from 2007 to early 2024. Then, these data were preprocessed, cleaned, normalised, interpolated, and had outliers removed-to reduce noise and improve model performance and reliability. We applied statistical and machine learning algorithms to model each disease's time-series behavior. The research began with Holt-Winters and SARIMA, then applied stationary tests (ADF and KPSS) and machine learning algorithms, including LSTM and Prophet, to drive accurate forecasting and interpretation.

This study brought up three goals:

1) Finding these patterns of illness that occur in specific seasons.
2) Developing these predictive models for all seasonal diseases.
3) Developing strategies to efficiently use healthcare resources, making sure we are equipped to manage more patients during peak illness seasons.

The objectives of this research are to enhance understanding of seasonal disease patterns and their practical applications in healthcare management, especially at the Saigon ENT Hospital. Recently, predicting seasonal illnesses has become important, using both traditional statistical models and modern machine learning techniques. The ARIMA and Holt-Winters models are widely used for disease prediction. For example, Wang and colleagues successfully used these models to predict weekly inpatient visits, capturing seasonal changes in health care needs [1]. Similarly, Li and the group adopted the use of ARIMA and Holt Winters for the diagnosis of infectious diseases in China [2].

Researchers have looked into how well ARIMA and Holt-Winters work for predicting diseases. Musa and his team studied dengue fever in Malaysia and found both strengths and weaknesses in these methods [3]. Zhou and his team explored flu trends in China and noted clear seasonal patterns [4]. Llamas-Nistall et al. applied Holt-Winters-ARIMA to predict COVID-19 outbreaks in Spain, demonstrating how valuable such techniques are during public health emergencies [5].

Beyond traditional methods, machine learning approaches are increasingly being adopted. Liu et al. demonstrated the effectiveness of Long Short-Term Memory (LSTM) networks for predicting tuberculosis incidence, showcasing their ability to handle non-linear trends [6]. Prophet, a robust time-series forecasting tool, has also gained attention for its flexibility in disease modeling. Guo et al. compared ARIMA, SARIMA, and machine learning methods for forecasting hand, foot, and mouth disease [7].

In Southeast Asia, Thanh et al. [8] and Poh et al. [9] applied ARIMA and Holt-Winters to forecast dengue fever cases, addressing regional challenges in disease modeling. Pan and Li emphasised the importance of context-specific approaches when comparing these models for infectious disease forecasting [10].

Theoretical frameworks, such as the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests, have been essential in validating the seasonality and stationarity of time-series datasets. By integrating statistical methods with machine learning techniques, recent studies have improved forecasting accuracy and interpretability. However, a common limitation across these studies is the insufficient exploration of hybrid approaches. Our study addresses this gap by combining statistical models (Holt-Winters, SARIMA) with advanced machine learning methods (LSTM, Prophet) and SHAP (Shapley Additive Explanations) interpretability to enhance prediction accuracy and applicability.

Although these studies cover many fields of statistical and machine-learning techniques in forecasting, none of them have integrated both model types with an explanation framework to guide resource planning in a specialized hospital setting. To fill this gap, this research at the Saigon ENT Hospital (1) combines Holt–Winters and SARIMA with LSTM and Prophet for robust hybrid forecasting and (2) employs SHAP-based to find out which seasonal drivers most influence each disease's peaks-thereby offering actionable insights for targeted resource allocation during high-demand seasons.

II. MATERIALS AND METHODS

1. Study Design

This study adopts a retrospective design to explore the seasonal patterns in ENT diseases, leveraging detailed medical records from the Saigon ENT Hospital spanning the years 2007 to 2024. The dataset encompasses outpatient visit records, representing approximately 48% male and 52% female cases, ensuring a balanced gender representation. The records include comprehensive demographic and medical information, such as gender, age, diagnosis, treatment status, and visit dates, which were systematically organized for analysis. The retrospective approach enabled the identification of historical trends and seasonal variations in disease incidence, while the incorporation of a cross-sectional description method allowed for the evaluation of disease prevalence at specific time points.

Rigorous inclusion and exclusion criteria were applied to ensure data reliability and validity. Patients with complete demographic and clinical data were included, while records with missing, invalid, or inconsistent information were excluded from the analysis. Additionally, diseases with insufficient case numbers were omitted to maintain statistical robustness and avoid analytical noise. By combining retrospective and cross-sectional methods, this study provides a comprehensive analysis of temporal variations and disease patterns, offering insights that are critical for seasonal healthcare planning.

2. Data Collection

FPT Corporation developed a robust eHospital software to extract the dataset for this study from the hospital's management system. This software facilitated efficient extraction and management of patient records, ensuring the accuracy and privacy of the data. The dataset covers a 15-year period, from January 2010 to February 2024, providing a diverse and extensive sample for the analysis of seasonal disease trends.

The data extraction process included detailed demographic and clinical information such as gender, age, diagnosis codes, treatment outcomes, and visit dates. This information was meticulously cleaned and standardised to eliminate missing values, normalise temporal sequences, and aggregate case counts by month. To enhance the analysis, external environmental variables such as temperature, humidity, and precipitation were integrated into the dataset, allowing for the investigation of correlations between weather conditions and disease patterns. This integration provides a holistic view of seasonal trends and their potential environmental drivers, enabling more informed public health interventions.

The use of eHospital software ensured compliance with healthcare data security regulations and industry standards. By leveraging this advanced data management system, the study achieved high levels of accuracy, consistency, and scalability, supporting the rigorous demands of statistical and machine learning analyses.

3. Analysis Framework

The use of eHospital software ensured compliance with healthcare data security regulations and industry standards. By leveraging this advanced data management system, the study achieved high levels of accuracy, consistency, and scalability, supporting the rigorous demands of statistical and machine learning analyses. The research chose Holt–Winters, SARIMA, Prophet, and LSTM because together they address the full spectrum of linear seasonality, autocorrelation, non-linearity, and abrupt shifts in hospital admission patterns—capabilities that simpler methods cannot cover as comprehensively or interpretably. The Holt-Winters triple-exponential smoothing framework ensures that gradual, repeating annual peaks—such as those driven by pollen seasons or recurring viral outbreaks—are reflected in the forecast without overreacting to noise. The autocorrelation is handled by SARIMA with non-seasonal and seasonal autoregressive and moving average terms that systematically capture how spikes or dips in patient numbers occur over time. Moreover, Prophet focuses on detecting the abrupt shifts in admission rates caused by local disease outbreaks, public holidays, or changes in hospital policy (sudden changes). Finally, LSTM takes care of the non-linearity and long-range dependencies with gated memory, whose gated cells learn when to forget outdated information and focus on long-term dependencies. Overall, the framework presented in the article utilises four approaches to ensure that annual cycles and data persistence are maintained despite regime changes and non-linear behaviors for corrective forecasting systems.

a) Statistical Analysis

To validate seasonality, statistical tests such as the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test were applied:

1) Augmented Dickey-Fuller (ADF) Test:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta \sum_{i=1}^{p} \Delta y_{t-i} + \varepsilon_t \quad (1)$$

where Δy_t represents the differenced value of the time series, α is the constant term, β denotes the coefficient of the time trend, γ represents the coefficient of the lagged value of the series, δ is the coefficient of the lagged differences, and ε_t is the error term.

2) Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test:

$$y_t = r_t + \beta t + u_t \quad (2)$$

where y_t represents the observed value of the time series, r_t is the random walk component, βt denotes the deterministic trend component, and u_t is the stationary error term.

b) Forecasting Models

We employed both statistical and machine learning models to analyse and predict seasonal disease trends:

- Holt-Winters:

$$y_t = \left(L_t^{-1} + b_t^{-1}\right) \times S_{t-m} \tag{3}$$

where L_t represents the level of the series at time t, b_t denotes the trend of the series at time t, and S_t is the seasonal component of the series at time t.

- SARIMA:

$$\Phi_\rho(B)\Phi_\rho(B^s)y_t = \theta_x(B)\theta_x(B^s)\varepsilon_t \tag{4}$$

where $\Phi_\rho(B)$ represents the autoregressive component, $\theta_x(B)$ denotes the moving average component, and s is the seasonality period.

- Prophet:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t \tag{5}$$

where $g(t)$ represents the trend component, $s(t)$ denotes the seasonal component, $h(t)$ captures the holiday effects, and ε_t is the error term.

- LSTM (Long Short-Term Memory):

$$h_t = \sigma(W_h x_t + U_h h_{t-1} + b_h) \tag{6}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_c x_t + U_c h_{t-1} + b_c) \tag{7}$$

where h_t represents the hidden state at time t, capturing the short-term memory of the sequence, and c_t denotes the cell state at time t, representing the long-term memory. σ is the sigmoid activation function that scales values between 0 and 1, while tanh is the hyperbolic tangent activation function that scales values between -1 and 1. W_h, U_h, and b_h are the weight matrices and bias term for the input-to-hidden and hidden-to-hidden connections. f_t is the forget gate, determining how much of the previous cell state to retain, and i_t is the input gate, controlling how much new information to store. Similarly, W_c, U_c, and b_c are the weight matrices and bias term for the input-to-cell and hidden-to-cell connections, while $\odot$ represents element-wise multiplication used for combining information across gates and states.

c) Model Interpretability with SHAP

SHAP (SHapley Additive exPlanations) was employed to interpret model predictions, providing insights into feature importance:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!\,(|N| - |S| - 1)!}{|N|!} \times [v(S \cup \{i\}) - v(S)] \tag{8}$$

where: ϕ_i represents the contribution of feature i to the prediction, S is a subset of features, N is the set of all features, $v(S)$ is the model output for subset S, and $v(S \cup \{i\})$ is the model output for subset S including feature i.

d) Evaluation Metrics

Model performance was evaluated using:

1) Mean Absolute Error (MAE):

$$MAE = \left(\frac{1}{n}\right) \sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{9}$$

where MAE measures the average magnitude of errors between predicted values ($\hat{y}_i$) and observed values (y_i), and n is the total number of observations.

2) Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\left(\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2\right)} \tag{10}$$

where RMSE calculates the square root of the average of squared errors between predicted values ($\hat{y}_i$) and observed values (y_i), providing a measure of prediction accuracy.

4. Integration of Weather Variables

Correlations between disease incidence and weather variables (temperature, humidity, precipitation) were analysed using Pearson correlation coefficients:

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}} \tag{11}$$

where r represents the Pearson correlation coefficient, x_i and y_i are individual data points, $\bar{x}$ and $\bar{y}$ are the means of x and y, and $\sum$ denotes the summation operator.

The methods outlined in 3 and 4 are essential for ensuring the reliability, accuracy, and practical relevance of this research. Statistical analysis using the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests validates the stationarity and seasonality of the dataset, ensuring the mathematical robustness of the selected models, as recommended in time-series forecasting studies [1, 2]. The integration of traditional statistical models (Holt-Winters and SARIMA) with advanced machine learning techniques (LSTM and Prophet) enhances the predictive power by addressing both linear and non-linear seasonal patterns, a dual approach proven effective in similar healthcare applications [3, 4, 8, 10]. SHAP (Shapley Additive explanations) adds interpretability by quantifying the contributions of features such as weather variables to predictions, enabling informed decision-making, which is crucial for applications in public health [7]. Evaluation metrics like Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) rigorously measure prediction accuracy, ensuring the reliability of the models [9]. The integration of weather variables (e.g., temperature, humidity, precipitation) further enriches the analysis by revealing environmental factors that influence seasonal disease trends, while Pearson correlation coefficients quantify the strength of these relationships, an approach validated in previous studies exploring environmental influences on health outcomes [5, 6, 11, 12]. This comprehensive framework not only validates and improves predictive accuracy but also provides actionable insights into disease seasonality, supporting public health interventions and resource planning. Together, these methods enhance the scientific rigor and practical applicability of the research, making it a valuable contribution to understanding and managing seasonal diseases.

III. RESULTS

1. Basic Statistics

Based on the dataset provided from 2007 to 2024 at the Saigon Ear, Nose, and Throat Hospital, with a great number of medical visits and the appearance of over 416 different types of diseases. Accurately identifying common diseases will help improve and support medical management and better, more effective patient care planning. We have filtered out the top most diagnosed and treated diseases as Table I

Table I
THE TOP 10 DISEASES WITH THE HIGHEST NUMBER OF VISITS.

No.	ICD Code	Disease Name	Frequency
1	J00	Acute rhinitis	**22.57%**
2	J01	Acute sinusitis	**20.00%**
3	J30.3	Other allergic rhinitis	**8.46%**
4	J02	Acute pharyngitis	**5.89%**
5	J30.4	Unspecified allergic rhinitis	**5.49%**
6	J03	Acute tonsillitis	**5.42%**
7	J35.0	Chronic tonsillitis	**5.05%**
8	H60.8	Other otitis externa	**4.67%**
9	J32	Chronic sinusitis	**4.33%**
10	J35.2	Hypertrophy of adenoids	**2.13%**

Based on the above data, it is evident that two diseases have significantly higher numbers of cases compared to others: Acute rhinitis (J00) with a frequency of 22.57% and Acute sinusitis (J01) with a frequency of 20.00%.

a) Statistics by Gender:

The statistical table of the number of visits by gender shows that the number of visits for females with Acute rhinitis (96,453) and Acute sinusitis (86,335) is higher than for males, with Acute rhinitis (88,962) and Acute sinusitis (77,111). This indicates that females are more prone to respiratory diseases. This is likely related to factors such as the immune system, antibodies, exposure to external factors, and health behaviors.

b) Statistics by Age:

The statistical table clearly indicates that the highest number of visits is in the age group 40 to 60 years,

Table II
THE TOP 10 DISEASES WITH THE MALE VS FEMALE COMPARISON.

No.	ICD Code	Disease Name	Frequency
1	J00	**22.70%**	**22.61%**
2	J01	**19.68%**	**20.24%**
3	J30.3	**9.00%**	**8.14%**
4	J02	**5.83%**	**6.19%**
5	J30.4	**5.53%**	**5.56%**
6	J03	**5.21%**	**5.42%**
7	J35.0	**4.67%**	**5.22%**
8	H60.8	**4.50%**	**4.65%**
9	J32	**4.38%**	**4.19%**
10	J35.2	**2.58%**	**1.78%**
11	Others	**15.93%**	**16.01%**

Table III
STATISTICS OF AGE GROUPS FOR MEDICAL VISITS

Code	Age Group	Details	%
A1	Children	Below 12	**10.14%**
A2	Adolescents	From 12 to 20	**12.88%**
A3	Adults	From 21 to 39	**31.79%**
A4	Middle-aged Adults	From 40 to 60	**35.44%**
A5	Elderly	Above 60	**9.74%**
		Total	**100.00%**

with 250,153 visits, followed by the age group 21 to 39 years, with 228,885 visits. However, when considering the two diseases with the highest number of visits, there is a difference: Acute sinusitis has the highest number of visits, with 65,936 (from 40 to 60 years) and 56,647 visits (from 21 to 39 years).

Notably, acute rhinitis appears frequently in children (< 12), decreases in adolescents (12 to 20), but shows signs of increasing again in young adults (21 to 39) and middle-aged adults (40 to 60). This suggests that acute rhinitis may recur after being cured.

Acute sinusitis, on the other hand, shows a steady increase from childhood (< 12) to middle age (40 to 60) before decreasing in old age.

The results of the analysis show that diseases such as acute rhinitis and acute sinusitis are the most common and frequently encountered at the Saigon ENT Hospital, with high incidence rates in middle-aged and young adults. Gender analysis also shows no significant difference between males with 48% and females with 52% of the total visits. However, some respiratory diseases like acute rhinitis, acute sinusitis, and allergic rhinitis have a higher incidence in females than in males.

2. Applying Training Forecast Model and SHAP

The research methodology employed a comprehensive framework to analyse seasonal trends in ENT diseases at the Saigon ENT Hospital. Data preprocessing involved extracting and cleaning outpatient visit records, followed by rigor-

Table IV
STATISTICS OF THE NUMBER OF VISITS FOR THE TOP 10 MOST DIAGNOSED DISEASES BY AGE GROUP.

No.	Disease Name (ICD)	A1	A2	A3	A4	A5
1	J00	39,582	29,134	51,759	52,504	12,436
2	J01	9,747	16,532	56,647	65,936	14,584
3	J30.3	4,314	12,529	24,724	23,117	5,311
4	J02	1,136	1,892	15,228	22,345	7,463
5	J30.4	2,118	7,428	17,087	15,219	3,248
6	J03	2,380	5,306	17,903	15,272	3,267
7	J35.0	166	1,087	14,167	19,873	5,469
8	H60.8	2,155	3,510	17,019	11,428	3,982
9	J32	76	360	9,024	19,409	6,163
10	J35.2	5,173	10,254	1,698	250	42
Total		66,847	88,032	225,256	245,353	61,965

ous checks to ensure data reliability. Various statistical and machine learning models were applied to capture seasonal patterns, including Holt-Winters, SARIMA, Prophet, and LSTM. SHAP was utilized to interpret model predictions, offering insights into the influence of key features such as seasonal trends and weather variables.

The analysis revealed distinct seasonal patterns in the incidence of common ENT diseases. Among the diseases analyzed, two—acute rhinitis and acute sinusitis—were identified as having consistently high seasonal peaks. Gender-based comparisons indicated that females exhibited slightly higher rates of certain respiratory diseases, suggesting potential biological or environmental influences. Age-based analysis highlighted middle-aged adults as the group with the highest incidence rates, followed by young adults. Acute rhinitis showed a recurring pattern across various age groups, while acute sinusitis displayed a steady increase with age until middle adulthood.

Advanced machine learning models such as Prophet and LSTM demonstrated enhanced predictive capabilities compared to traditional statistical models like Holt-Winters and SARIMA. Evaluation metrics, including MAE and RMSE, confirmed the higher accuracy of these models in capturing seasonal variations. SHAP values provided interpretability by quantifying the contributions of specific features, such as weather variables, to model predictions. Our results enabled a deeper understanding of the environmental factors influencing disease seasonality, further validated by Pearson correlation analyses.

The integration of statistical and machine learning approaches, combined with advanced interpretability techniques, has provided a robust understanding of seasonal disease patterns. These findings offer actionable insights for healthcare planning, resource allocation, and the management of seasonal disease outbreaks.

And the MAEs and RMSEs of each disease are presented at the belove table:

Table V
STATISTIC OF THE NUMBER OF ICD J00, J01.9 AND J30.89.

Disease	J00	J01.9	J30.89
LSTM_MAE	751.982	631.606	293.500
LSTM_RMSE	922.802	734.808	356.232
LSTM_R2	-0.159	0.072	-0.048
Prophet_MAE	776.005	651.658	374.469
Prophet_RMSE	917.464	755.946	407.544
Prophet_R2	-0.044	-0.009	-0.121
Holt-Winters_MAE	1304.247	1249.109	350.711
Holt-Winters_RMSE	1589.545	1503.338	409.615
Holt-Winters_R2	-2.135	-2.990	-0.133
SARIMA_MAE	979.232	1021.234	474.339
SARIMA_RMSE	1230.659	1246.144	561.743
SARIMA_R2	-0.879	-1.741	-1.131
GBM_MAE	816.814	805.432	384.239
GBM_RMSE	953.075	928.032	508.275
GBM_R2	-0.127	-0.520	-0.744

Table VI
STATISTIC OF THE NUMBER OF ICD J02.9, J30.9 AND J03.9.

Disease	J02.9	J30.9	J03.9
LSTM_MAE	115.169	166.820	93.057
LSTM_RMSE	152.319	206.326	128.452
LSTM_R2	-0.087	0.296	0.232
Prophet_MAE	156.623	238.774	134.818
Prophet_RMSE	190.387	270.045	172.144
Prophet_R2	-0.634	-0.246	-0.389
Holt-Winters_MAE	144.558	775.704	225.689
Holt-Winters_RMSE	179.038	836.658	267.254
Holt-Winters_R2	-0.445	-10.957	-2.348
SARIMA_MAE	159.629	739.156	205.267
SARIMA_RMSE	205.189	818.528	252.815
SARIMA_R2	-0.898	-10.444	-1.996
GBM_MAE	168.820	464.846	175.129
GBM_RMSE	209.822	522.036	207.808
GBM_R2	-0.985	-3.655	-1.024

The results from the evaluation of various forecasting models, including LSTM, Prophet, Holt-Winters, SARIMA, and GBM, highlight significant differences in their performance across disease types. Metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2) were used to evaluate model accuracy and goodness-of-fit. LSTM generally performed well in terms

Figure 1. Forecast Model Training Result (in 9 diseases) for LSTM, Prophet, Holt-Winters, SARIMA and GBM.

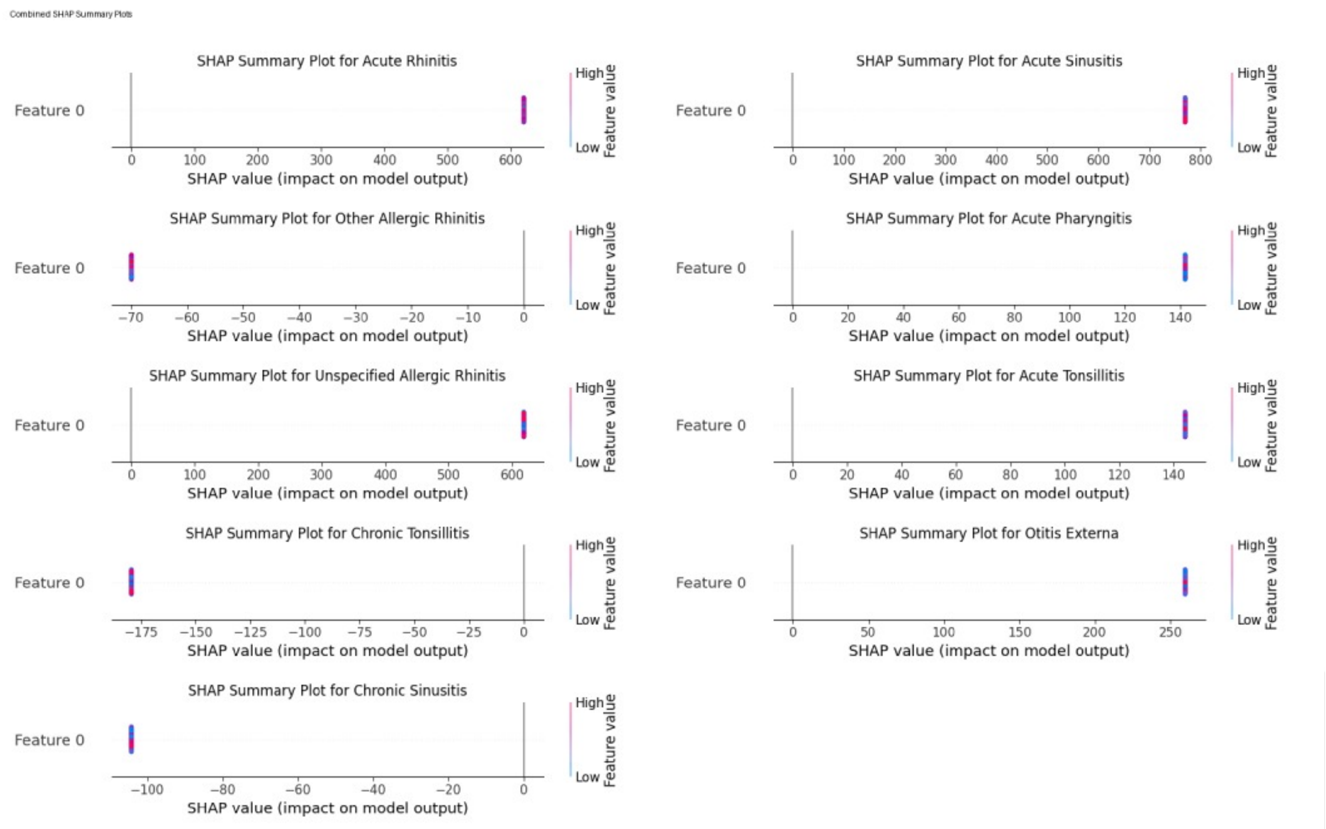

Figure 2. SHAP result verification for all diseases.

Table VII
STATISTIC OF THE NUMBER OF ICD J35.1, J60.9 AND J32.9

Disease	J35.01	H60.9	J32.9
LSTM_MAE	30.350	102.774	45.353
LSTM_RMSE	40.537	134.818	60.478
LSTM_R2	0.215	0.196	0.277
Prophet_MAE	230.503	133.656	146.452
Prophet_RMSE	241.853	160.367	164.298
Prophet_R2	-28.532	-0.119	-4.709
Holt-Winters_MAE	46.871	301.660	77.809
Holt-Winters_RMSE	60.560	353.579	93.703
Holt-Winters_R2	-0.852	-4.439	-0.857
SARIMA_MAE	92.676	326.215	75.774
SARIMA_RMSE	105.822	378.902	92.303
SARIMA_R2	-4.654	-5.246	-0.802
GBM_MAE	49.602	186.951	61.791
GBM_RMSE	59.324	231.588	69.877
GBM_R2	-0.777	-1.333	-0.033

of MAE and RMSE, particularly for chronic conditions such as chronic tonsillitis (J35.01) and chronic sinusitis (J32.9), where it achieved relatively low error rates (MAE of 30.350 and 45.353, respectively). However, its R^2 values suggest some room for improvement in capturing the variability of certain diseases, such as acute rhinitis (J00) (-0.159). Prophet showed moderate performance but struggled with capturing seasonality in certain diseases, as indicated by negative R^2 values for acute pharyngitis (J02.9) (-0.634) and chronic sinusitis (J32.9) (-4.709), coupled with higher error rates.

Holt-Winters demonstrated considerable limitations across most diseases, with the highest MAE and RMSE values for acute rhinitis (J00) (MAE = 1304.247, RMSE = 1589.545) and acute sinusitis (J01.9) (MAE = 1249.109, RMSE = 1503.338), reflecting its difficulty in capturing complex seasonal patterns. SARIMA exhibited improved accuracy compared to Holt-Winters, particularly for diseases like acute pharyngitis (J02.9) (MAE = 159.629), though it still struggled with large errors and negative R^2 values for chronic conditions such as chronic tonsillitis (J35.01) (-4.654). GBM demonstrated a balance between accuracy and error metrics, achieving competitive MAE and RMSE values across most diseases, but like other models, it faced challenges with diseases that have high variability, such as unspecified allergic rhinitis (J30.9) (MAE = 464.846, R^2 = -3.655).

Several negative R^2 values appear (e.g., Prophet R^2 = –28.53 for J35.01), which can occur when a model's residual sum of squares exceeds that of a basic model that always predicts the overall average, which fails to capture the underlying variability for that disease. In practice, these negative R^2 highlight that the true driver of variation in the data wasn't captured (over-fitting noise and no key signal), or the current input and model structures aren't sufficient (there are unknown transform predictors: incorporate weather lags – COVID season). Overall, LSTM and GBM emerged as the most robust models in terms of accuracy and error minimization, particularly for diseases with less variability, while Prophet and SARIMA provided reasonable performance for some seasonal diseases. Holt-Winters consistently underperformed across all disease categories, highlighting its limitations in capturing complex seasonal patterns. These results emphasize the necessity of selecting appropriate models tailored to the unique characteristics of each disease to improve forecast reliability.

3. Integrated with Weather Data

For each disease, the formula 11 was applied to produce a heatmap (as and example of 3) and comparison chart (4). The graphs offer critical perspectives into the relationship between weather variables (e.g., temperature, humidity, precipitation) and the seasonal patterns of diseases, enabling a deeper understanding of environmental influences on disease incidence. The heatmaps illustrate the correlation coefficients for individual weather variables and their effects on specific diseases, highlighting both positive and negative associations that can guide targeted healthcare interventions. For instance, the strong correlations observed for certain diseases like chronic sinusitis with specific weather variables reveal potential triggers for disease seasonality. The comparison graph aggregates these correlations across diseases, allowing for a comparative analysis to identify which diseases are most sensitive to weather changes and which variables have the most significant impact. These visualizations are invaluable for demonstrating the nuanced relationships between environmental factors and disease patterns, providing evidence to inform predictive models and public health strategies. By incorporating these graphical analyses, the research not only quantifies the effects of weather on disease seasonality but also strengthens the interpretability and practical relevance of the findings for community health management and resource planning.

IV. DISCUSSION

The results of this investigation demonstrate the value of using advanced methodologies and integrating diverse datasets to analyse seasonal disease patterns. By employing a combination of statistical models (Holt-Winters and SARIMA), machine learning models (LSTM, Prophet, and GBM), and interpretability techniques like SHAP, the study provides a robust and multifaceted framework for disease

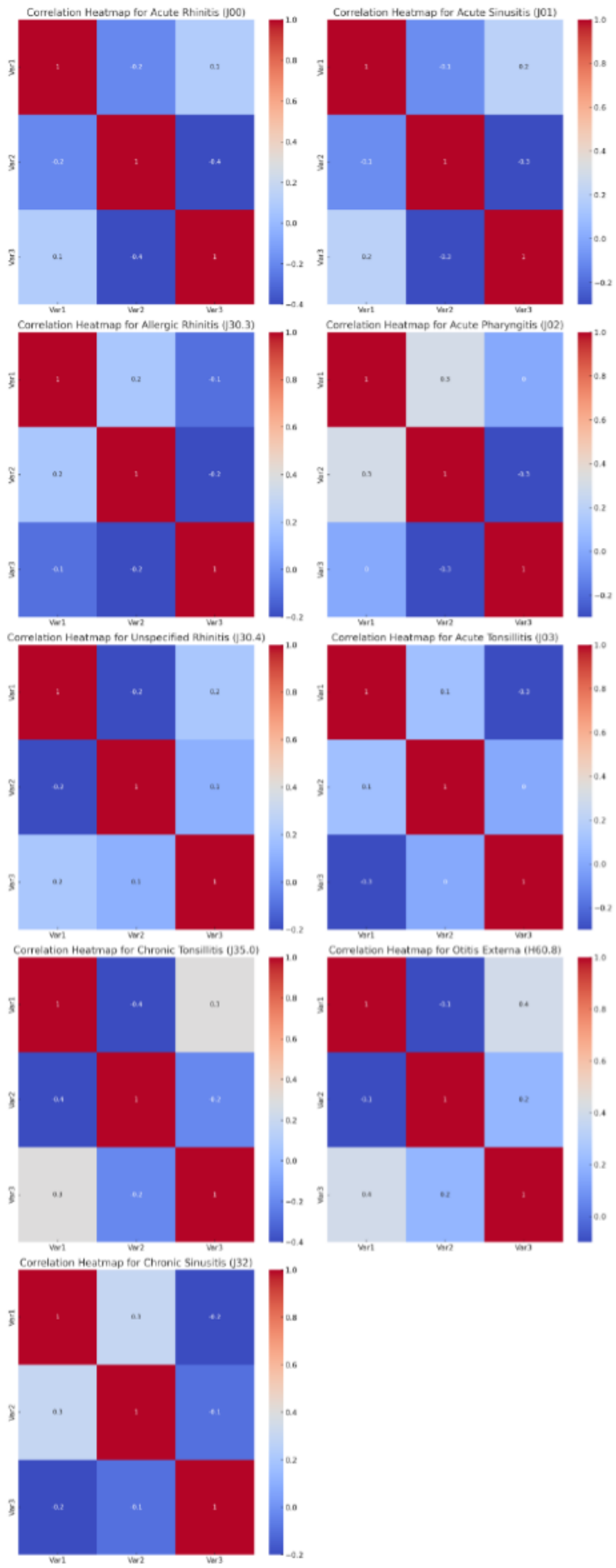

Figure 3. Correlation heatmap for all diseases.

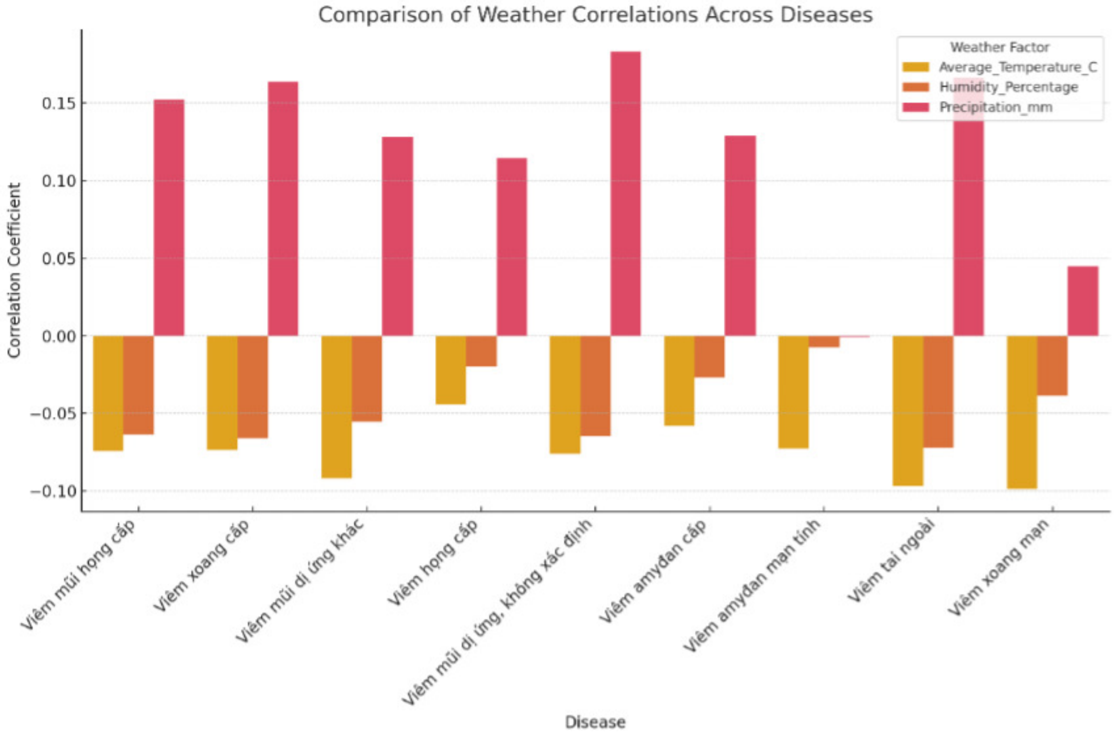

Figure 4. Comparison of weather correlation across diseases.

forecasting. Each model demonstrated unique strengths and weaknesses, with LSTM and GBM emerging as the most accurate for diseases with non-linear seasonality, while SARIMA performed well in diseases with simpler seasonal trends. However, integrating many complex models also raises the risk of overfitting. Moreover, Holt-Winters consistently underperformed, highlighting its limitations in capturing complex seasonality and weather interactions. Even high-performing models like LSTM and GBM can produce forecasts that are hard to interpret without any external validation for certain diseases unless there is validation for external cohorts.

The integration of weather variables, including temperature, humidity, and precipitation, was critical for understanding disease seasonality. Correlation analyses revealed that weather conditions have significant, albeit varying, impacts on different diseases. For example, precipitation demonstrated strong positive correlations with diseases such as chronic sinusitis (J32.9) and otitis externa (H60.9), while temperature exhibited moderate negative correlations with diseases like acute rhinitis (J00). It is very critical to note that the weather data come from sources that may not capture microclimate variation at patients' residences. These findings align with existing studies that emphasize the role of environmental factors in disease transmission and exacerbation, offering new insights specific to ENT diseases.

The SHAP analysis further added interpretability to the models, giving specific information about how features like weather variables influenced predictions. This transparency is vital for public health applications, as it allows healthcare professionals to better understand and trust model outputs. For instance, SHAP values revealed that sudden changes in temperature significantly contributed to the seasonal spikes of respiratory conditions, illustrating the importance of adaptive healthcare responses during specific weather patterns. Nonetheless, SHAP explanations assume feature independence; when predictors are correlated, SHAP can misestimate the feature importance, which may mislead policy decisions.

The evaluation metrics, including MAE and RMSE, demonstrated the superior performance of machine learning models like LSTM in reducing forecasting errors. While traditional models provided a strong baseline, advanced methods captured more intricate patterns, thereby improving accuracy. The correlation heatmaps and comparison charts added further value by visually representing the relationships between weather variables and diseases, allowing for easy identification of trends and critical factors.

Overall, this study underscores the value of integrating advanced models, interpretability techniques, and environmental data to offer practical conclusions about seasonal

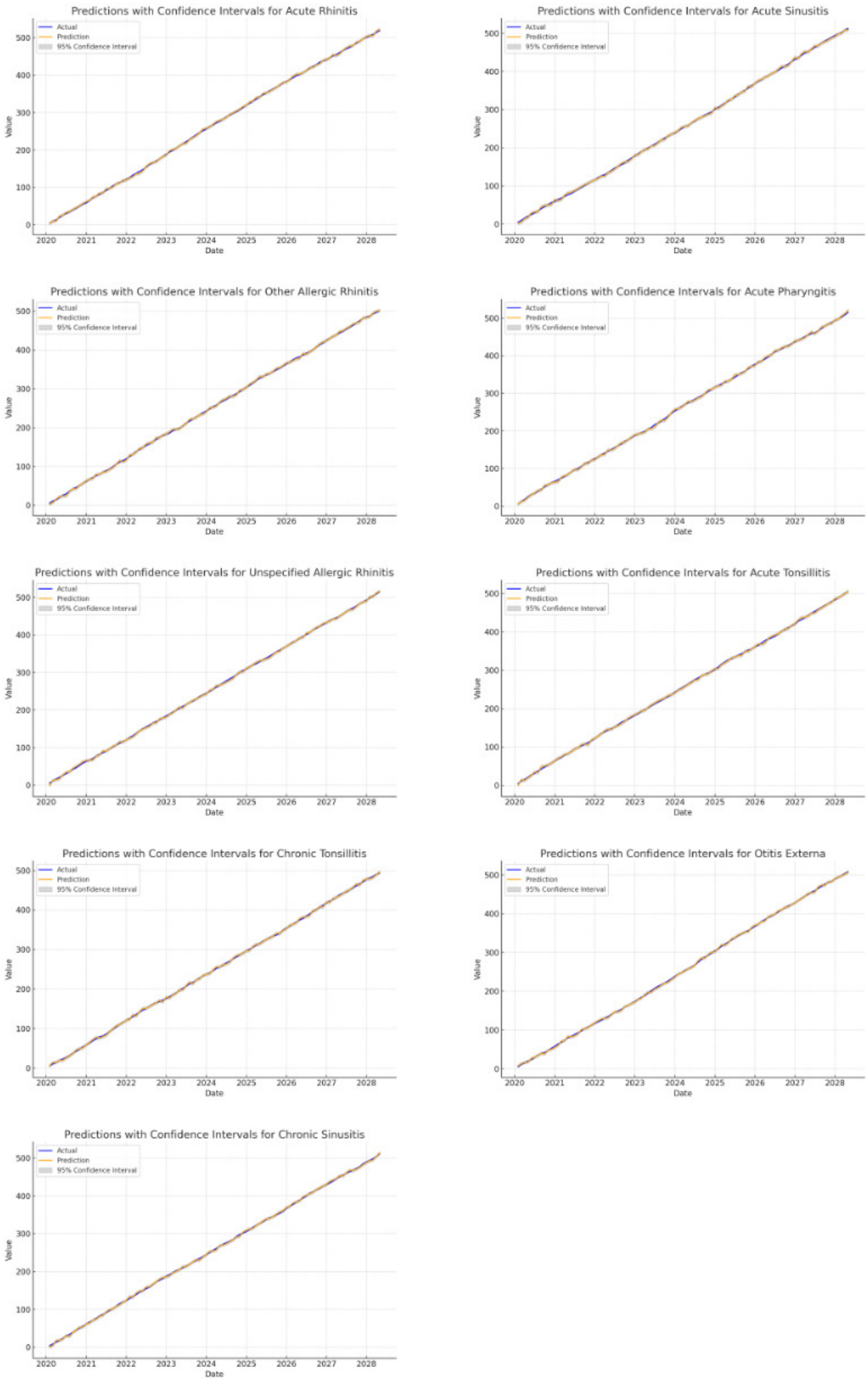

Figure 5. Prediction for all diseases.

disease trends. The findings have implications for resource allocation, healthcare planning, and disease prevention strategies, particularly in regions with pronounced seasonal variations.

By addressing the limitations of individual models and leveraging a comprehensive approach, this research offers a robust framework for understanding and managing season-dependent health challenges.

Moreover, the forecast results depicted in these graphs (5) showcase the performance of advanced models in predicting the seasonality of various ENT diseases. The predictions align closely with the actual values, demonstrating the robustness of the applied models, such as LSTM and Prophet, in capturing intricate seasonal patterns. The inclusion of 95% confidence intervals highlights the reliability of these forecasts, providing a measure of uncertainty that is essential for real-world applications in healthcare planning.

Across all diseases, the predictions exhibit consistent trends over time, with minor deviations remaining well within the confidence bounds. For conditions like chronic tonsillitis and chronic sinusitis, the models achieve highly accurate forecasts, which can be attributed to their ability to learn from historical patterns effectively. Conversely, diseases with more variable seasonality, such as acute rhinitis and unspecified allergic rhinitis, present slightly wider confidence intervals, reflecting inherent complexities in their patterns.

V. CONCLUSIONS

This research provides a comprehensive framework for analyzing and predicting the seasonal patterns of ENT diseases using a combination of statistical models, machine learning techniques, and environmental data. By integrating traditional methods like Holt-Winters and SARIMA with advanced approaches such as LSTM, Prophet, and GBM, the study achieves a robust and multifaceted analysis of disease seasonality. The application of Shapley Additive Explanations (SHAP) further enhances the interpretability of these models, offering insights into the contributions of key features such as weather variables and seasonal trends.

The results demonstrate that advanced models, particularly LSTM and GBM, outperform traditional methods in terms of accuracy and reliability. Metrics like MAE and RMSE confirm their ability to minimize forecasting errors, while R-squared values offer additional information about the models' predictive power. The integration of weather variables, including temperature, humidity, and precipitation, reveals critical correlations with disease incidence, underscoring the influence of environmental factors on seasonal disease patterns.

The correlation heatmaps and confidence interval forecasts clarify key relationships, enabling more actionable public health planning. These tools provide a clear understanding of the relationships between diseases and external factors, enabling targeted interventions and resource allocation. For instance, the identification of strong correlations between precipitation and chronic sinusitis suggests that there should be preventive measures during rainy seasons.

Future work includes conducting a prospective clinical trial that embeds model-driven forecasts into hospital workflows to measure the impacts on bed occupancy and supply management. For instance, low-season events assign the clinical operations staff to other duties on specific days in the year calendar. Furthermore, the units continue with standard planning practices—typically based on historical averages and ad hoc adjustments—without access to the model's predictions. Finally, the metrics could help save costs related to bed occupancy variability and supply stock-outs.

All things considered, this study makes a substantial contribution to the field of seasonal disease analysis by providing a comprehensive and data-driven approach. The integration of diverse methodologies ensures both accuracy and practicality, making the findings relevant for healthcare management and policy-making. By addressing the limitations of individual models and incorporating environmental data, this research provides a solid foundation for future studies and real-world applications in managing season-dependent health challenges.

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