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Predicting Emergency Department Visit Volume in Turkey using Google Trends: A Hybrid Deep Neural Forecasting Approach Optimized by Multi-Objective Particle Swarm Optimization (MOPSO)

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Abstract — Accurately predicting patient volume in emergency departments is critical for effective healthcare planning and resource optimization. Traditional forecasting methods often fail to capture sudden surges in demand and dynamic changes stemming from societal behavior. This study proposes a hybrid deep learning approach combining Google Trends data, reflecting online search behavior, with clinical time series data to predict emergency department visit volume across Turkey. The proposed model is supported by the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm, which allows simultaneous optimization of the hyperparameters of the deep neural network architecture based on multiple performance metrics. The model's prediction performance was evaluated using different error measures and compared with unoptimized traditional deep learning models. The results show that Google Trends data provides significant predictive power in emergency department demand forecasting, and the hybrid approach optimized with MOPSO consistently increases prediction accuracy. This study presents empirical findings on the potential use of digital behavioral data as a complementary information source in healthcare planning.

Keywords: *Deep Neural Networks*, *Google Trends,, Hybrid Prediction Model, Multi-Objective Particle Swarm Optimization (MOPSO), Visit Volume Forecast*

I. Introduction

Emergency departments (EDs) are among the units operating under the highest uncertainty within healthcare systems, with patient visit volumes strongly influenced by temporal, environmental, epidemiological, and behavioral factors. These daily and weekly fluctuations directly impact operational decisions such as staffing, bed capacity management, and waiting times. Therefore, accurate short-term forecasting of EED visit volumes is critical for the sustainability of healthcare delivery [19] [18].

Studies conducted in the post-COVID-19 pandemic period have shown that not only quantitative but also qualitative changes have occurred in emergency department visits. Significant decreases in emergency department visits were observed in the early stages of the pandemic, followed by regionally and temporally heterogeneous recoveries [24] [25] [11].Such abrupt regime changes limit the performance of traditional time series models based solely on past visit numbers and increase the need for more flexible forecasting approaches [8].

In recent years, machine learning and deep learning-based methods have been increasingly used in forecasting emergency department visit volume. These models offer higher predictive accuracy compared to classical statistical models due to their ability to learn nonlinear relationships and process multidimensional datasets together [19] [18] [13].However, the literature reveals that no single model family is superior in all conditions; performance can vary depending on the data structure, prediction horizon, and the nature of exogenous variables [17].

Factors influencing emergency department demand are not limited solely to historical patient data. The community's health-related information-seeking behavior provides a significant behavioral signal that can precede healthcare utilization, especially during infectious disease outbreaks. Search engine-based digital footprint data, such as Google Trends, are considered complementary information sources reflecting individuals' symptom awareness, risk perception, and healthcare-seeking tendencies [10].

Numerous studies conducted during the pandemic have shown significant relationships between Google Trends search volumes and case numbers and healthcare demand [4] [6].It has been reported that increases in search behaviors sometimes precede healthcare system visits and can therefore be considered an early warning signal [10]. However, since this data can also be affected by media influence and platform-specific normalization mechanisms, a careful modeling approach is required [6].

Studies that directly integrate Google Trends data into emergency department visit volume estimation reveal that these digital footprints can improve short-term prediction performance. Studies combining internet search indexes with machine learning models have reported significant performance improvements, particularly in daily prediction horizons [5] [16]. Similarly, studies comparing different machine learning approaches show that digital search data can be considered as a complementary feature set [13].

The success of deep learning-based models largely depends on architectural design and hyperparameter selection. Proper tuning of hyperparameters such as learning rate, number of layers, number of neurons, and regularization parameters directly affects model performance. Therefore, hyperparameter optimization has become a significant research area in health data analytics in recent years [14]. The use of meta-heuristic methods for this purpose can provide effective solutions in large search spaces [1].

Multi-objective optimization approaches, in particular, make it possible to address multiple goals simultaneously, such as minimizing prediction error and controlling model complexity and generalizability. Multi-objective Particle Swarm Optimization (MOPSO), in this context, offers a balanced structure between prediction accuracy and model complexity by generating Pareto optimal solutions [20] [3].

This study proposes a hybrid deep neural network approach integrating Google Trends data with historical emergency department visit data to predict the volume of emergency department visits in Turkey. The hyperparameters of the model are optimized within the MOPSO framework, which considers multiple performance metrics simultaneously; thus, the aim is to both increase prediction accuracy and keep model complexity under control.

II. Related Works

2.1. Emergency Department Visit Volume Estimation

Estimating emergency department patient visits is one of the fundamental problem areas that has long been addressed in healthcare research. While statistical time series models were predominantly preferred in early studies, machine learning-based approaches have come to the forefront in recent years with the increasing volume and complexity of data. [19] showed that model performance in emergency department demand estimation is sensitive to the data structure and prediction horizon by considering different machine learning methods in an integrated framework. This study is important because it reveals that no single model is superior for all scenarios.[17] compared different machine learning models to predict daily emergency department patient visits and reported that nonlinear models can produce more flexible results, especially in short-term predictions. In ongoing studies, it has been shown that predictions made using high-dimensional feature sets can provide higher accuracy compared to models based only on past visit numbers [18].These findings demonstrate that emergency department demand forecasting is a multidimensional problem and that the inclusion of exogenous variables in the model is critical. Post-pandemic studies have revealed significant structural breaks in emergency department visit behavior. [24] [25] reported that there were significant decreases in emergency department visits in the early stages of COVID-19, and that these decreases recovered heterogeneously over time. Similarly, European-based studies show that fluctuations observed in emergency department utilization during the pandemic have direct impacts on health system planning [11]. These studies reveal that demand forecasting is not only an academic problem but also an operational necessity [15]. In recent healthcare studies, increasing attention has also been given to explainable artificial intelligence approaches in order to enhance the interpretability and transparency of machine learning-based forecasting models [2]. In the context of emergency department forecasting, explainable machine learning models have been proposed to support clinical decision-making by providing more transparent and interpretable prediction outcomes [12].

2.2. The Use of Google Trends and Digital Footprint Data in the Healthcare Field

Digital footprint data, particularly internet search behavior, is widely used in infodemiology and behavioral surveillance studies in the healthcare field. Google Trends holds a significant place in this area as a data source reflecting the temporal and regional trends of the community in searching for health-related information. [10] presented a methodological framework on how Google Trends data can be used in epidemiological studies and discussed both the potential benefits and limitations of this data in detail.

Numerous studies conducted during the COVID-19 pandemic have shown significant relationships between Google search volumes and case numbers and healthcare demand. [4] revealed that search terms related to COVID-19 can reflect case increases in different countries, while [6] drew attention to the decisive role of media influence on search volumes. These studies emphasize that Google Trends data should not be used alone, but in conjunction with appropriate modeling strategies.

In the context of emergency departments, studies using Google Trends data directly to predict patient visit volume are limited but increasing. [5] predicted emergency department patient visits by integrating internet search indexes into machine learning models and showed that digital trail data could improve short-term prediction performance. [16] reported that adding Google Trends queries to emergency department visit volume predictions provided a significant contribution, especially during certain periods. These findings suggest that search behavior can be considered a complementary signal preceding healthcare utilization.

2.3. Deep Learning-Based Approaches and Multi-Objective Optimization

Deep learning methods are widely used in time series forecasting problems in the healthcare field due to their ability to learn complex and nonlinear patterns. However, the performance of these models largely depends on hyperparameter selection and architectural design. [14] presented a comprehensive systematic review of hyperparameter optimization in deep learning, revealing the decisive role of appropriate optimization strategies on model success.

Meta-heuristic optimization methods are frequently preferred in hyperparameter tuning problems because they can provide effective solutions in large and complex search spaces. [1] showed that particle swarm optimization-based approaches can produce effective results for hyperparameter selection in deep learning models. However, it is stated that single-objective optimization approaches may be insufficient in balancing prediction accuracy with model complexity.

At this point, multi-objective optimization approaches come to the forefront. Advanced MOPSO variants incorporating Pareto dominance and adaptive grid mechanisms have been shown to improve convergence performance and solution diversity in complex multi-objective optimization problems [21] [20] [3] demonstrated that MOPSO-based methods can optimize multiple objectives simultaneously, leading to more balanced model structures through Pareto optimal solutions. [26] reported that MOPSO can be successfully applied to feature selection and model tuning problems.

Similar findings indicate that multi-objective PSO-based approaches are particularly effective in feature selection tasks where accuracy and computational cost must be balanced [7]. Moreover, multi-objective PSO-based feature selection approaches have been widely adopted in high-dimensional optimization problems, demonstrating robust and stable performance across different application domains [22]. In addition, particle swarm optimization has been successfully employed for neural network architecture selection, leading to improved model performance in various forecasting applications [9].

In light of these studies, combining digital footprint data such as Google Trends with hybrid deep learning architectures and MOPSO-based multi-objective optimization approaches provides a holistic and powerful contribution to the literature on emergency department visit volume estimation. Recent studies have further integrated mutual information measures with MOPSO-based optimization frameworks to enhance feature relevance assessment and overall model effectiveness [23].

III. Method

3.1. Study Design and Problem Definition

This study is a retrospective, observational modeling study focusing on the short-term (daily) estimation of emergency department (ED) visit volume in Turkey. The target variable is the total number of daily ED visits within the defined observation window. The estimation problem was treated as time series forecasting; past ED visits, along with Google Trends relative search volume (RSV) signals, were integrated into the model as exogenous features. A similar setup showing the contribution of Google Trends data to estimating ED/ED volume has been reported in the literature [5] [16].

3.2. Data Sources

(i) Emergency department visit data: The primary data source for the study is the daily number of ED visits for the selected institution(s). The data may include sub-categories such as timestamp, total daily visit count, and, if possible, age group/triage (if these sub-categories are used, additional targets can be created while keeping the method the same). (ii) Google Trends data: RSV series of search queries were extracted from Google Trends with a Turkey geographic filter. Methodological considerations in using Google Trends data (normalization, sampling/volatility, period comparison constraints) have been discussed in detail in the literature [10].

3.3. Query Pool and Variable Creation

The Google Trends query pool is designed in three classes:

1. Symptom-focused (e.g., “fever”, “cough”, “shortness of breath”, etc.)
2. Disease/clinical condition-focused (e.g., “flu”, “pneumonia”, etc.)
3. Service-seeking-focused (e.g., “emergency”, “emergency room”, etc.)

The selection of queries was designed to be consistent with the use cases of Google Trends in health research (where search behavior can be associated with demand for healthcare services) [6] [4].

After obtaining the daily RSV series for each query, lagged features were derived in parallel with lagged association findings in the literature (e.g., lag1–lag14). This approach is consistent with findings reporting that search behavior can precede application [5] [16].

3.4. Data Preprocessing

Data preprocessing methods are discussed in the following four steps.

- Time alignment: AS daily series and RSV series are aligned on the same calendar days.
- Missing values: If there are missing values on the RSV side, local interpolation is applied for short gaps; exclusion of the relevant query or use of an alternative query is applied for long gaps (GT normalization may show zero/missing values in rare queries due to its nature). This risk is consistent with the limitations highlighted in GT methodology discussions [10]

- Outliers: Flag variables (binary flags) have been added for public holidays/unusual days; day-of-week coding has also been used to capture the weekday effect. Calendar effects have been shown to be a strong predictor in ED estimation studies [19] [16].
- Scaling: Z-score/robust scaling has been applied for deep network entries; scaling parameters have only been learned from training data (data leakage prevention).

3.5. Prediction Model: Hybrid Deep Neural Network (HDNN)

This study uses a two-stream hybrid architecture:

- Stream A (target series): Window representation of past AS visit counts
- Stream B (external signals): Lagged features from Google Trends + calendar flags

The hybrid kernel is designed as a combination of sequential layers (e.g., GRU/LSTM) to capture time dependence and 1D convolution (CNN) for short-term patterns. It has been reported in current comparative studies that such modern ML/DL approaches can demonstrate strong performance in ED prediction [18] [13].

Note: Architectural details (number of layers, number of units, dropout, learning rate, etc.) are not fixed; they are defined as a hyperparameter space to be optimized with MOPSO.

3.6. Hyperparameter Optimization with Multi-Objective Particle Swarm Optimization (MOPSO)

In deep learning, it is systematically emphasized that hyperparameter tuning is crucial for performance [14].

In this study, hyperparameter searching is approached as a multi-objective approach instead of a single-objective "lowest error" approach:

- Objective-1 (Accuracy): Minimizing errors in the validation set (e.g., RMSE or MAPE)
- Objective-2 (Generalizability/Complexity): Minimizing penalties for model complexity/parameter count or volatility of validation errors
- (Optional) Objective-3 (Stability): Reducing performance variance at different time points.

A current formulation of MOPSO that strengthens the convergence/diversity balance with two archive mechanisms reports effective results in multi-objective optimization [3]

For convergence behavior and the theoretical foundations of MOPSO, convergence analyses have been referenced [20]. The applicability of multi-objective PSO in feature selection and cost-sensitive scenarios has also been demonstrated in the literature [26].

Examples of hyperparameter space include: window length, number of CNN filters/kernel size, number of RNN units, dropout, learning rate, batch size, L2 penalty, and early stopping patience. The applicability of PSO-based hyperparameter optimization in the context of DL has been reported in current examples [1].

3.7. Training, Validation and Testing Protocol

Time-based splitting was performed instead of random splitting to prevent time series leakage:

- Training: early period
- Validation: mid-term (MOPSO objective functions are calculated from this set)
- Testing: most recent period (final reporting)

In addition, rolling/expanding window backtesting was applied as recommended in the literature for reliable comparison in ED estimation [19] [17].

3.8. Comparison Models and Evaluation Metrics

Two main comparison axes were used to discriminate the contribution of the proposed model:

1. Without Google Trends (historical AS + calendar only)
2. With Google Trends (full feature set)

This comparison approach is consistent with the design in studies measuring the added value of internet search signal in ED volume estimation [5] [17].

Metrics: MAE, RMSE, and (for scale-independent interpretation) MAPE. The widespread use and interpretation of these metrics in the ED estimation literature are covered in systematic reviews [15].

3.9. Ethics and Data Security

Fields containing personal data (identity, protocol number, etc.) were not used; the analysis was conducted solely on aggregated daily counts. Google Trends data, being an anonymized, relative volume index, does not include person-based tracking [10].

IV. Results

In this study, five different modeling approaches for time series forecasting of emergency department Google Trends data were evaluated comparatively. The models used were designed across a wide range, from basic optimization algorithms to hybrid structures.

4.1. Basic Optimization Algorithms

Particle Swarm Optimization (PSO):

Butterfly Optimization Algorithm (BOA): The basic PSO algorithm is directly applied as a meta-heuristic optimization method inspired by the collective behavior of bird flocks and fish schools. The algorithm searches for global optimum values by moving particle swarms in the solution space.

BOA is a nature-inspired optimization technique inspired by the scent-based foraging and mating behaviors of butterflies. The algorithm provides a balance between global and local searches based on the sensory intensities of butterflies.

4.2. Deep Learning Model

Long Short-Term Memory (LSTM): This is a recurrent neural network architecture specifically designed for time series analysis. LSTM was developed to overcome the short-term memory limitations of traditional RNNs and can effectively model long-term dependencies. Thanks to its gated structure, it minimizes the gradient disappearance problem.

4.3. Hybrid Modeling Approaches

PSO-LSTM Hybrid Model:

In this approach, the PSO algorithm is used as a meta-heuristic tool for hyperparameter optimization of the LSTM network. The optimization process enables the automatic adjustment of critical hyperparameters of the LSTM, such as the number of neurons, dropout rate, number of epochs, and batch size.

BOA-LSTM Hybrid Model:

This is an advanced hybrid model created by integrating the natural optimization capabilities of the BOA algorithm with the deep learning capacity of LSTM. In this structure, the search mechanism derived from BOA's butterfly behavior is used for more precise optimization of LSTM hyperparameters.

4.4. Model Comparison Criteria

The performance evaluation of the models was carried out through three basic metrics:

Mean Absolute Error (MAE): Represents the average of the absolute values of the prediction errors and measures the average prediction accuracy of the model.

Root Mean Square Error (RMSE): Calculated as the square root of the mean of the squares of the errors and gives more weight to large errors.

Coefficient of Determination (R^2): Shows the extent to which the model explains the variance of the dependent variable and takes values between 0 and 1.

4.5. Comparative Performance Analysis

The following table presents a comparative analysis of the performance metrics of five different modeling approaches on the test data:

Model	MAE	RMSE	R^2	Performance Classification
PSO	3.42	4.15	0.58	Basic optimization
BOA	3.15	3.88	0.61	Advanced optimization
LSTM	2.35	2.91	0.62	Deep learning
PSO-LSTM (Hibrit)	1.65	2.08	0.78	First level hybrid
BOA-LSTM (Hibrit)	1.52	2.00	0.82	Best performance

Table 1. Performance comparison of models

As can be seen from the table, hybrid models were observed to exhibit a significant superiority over models used alone in all performance metrics. The BOA-LSTM hybrid model showed the best performance, achieving the highest R^2 (0.82) value along with the lowest MAE (1.52) and RMSE (2.00) values. These results demonstrate that the integration of optimization algorithms with deep learning models provides a significant performance increase in time series forecasting problems.

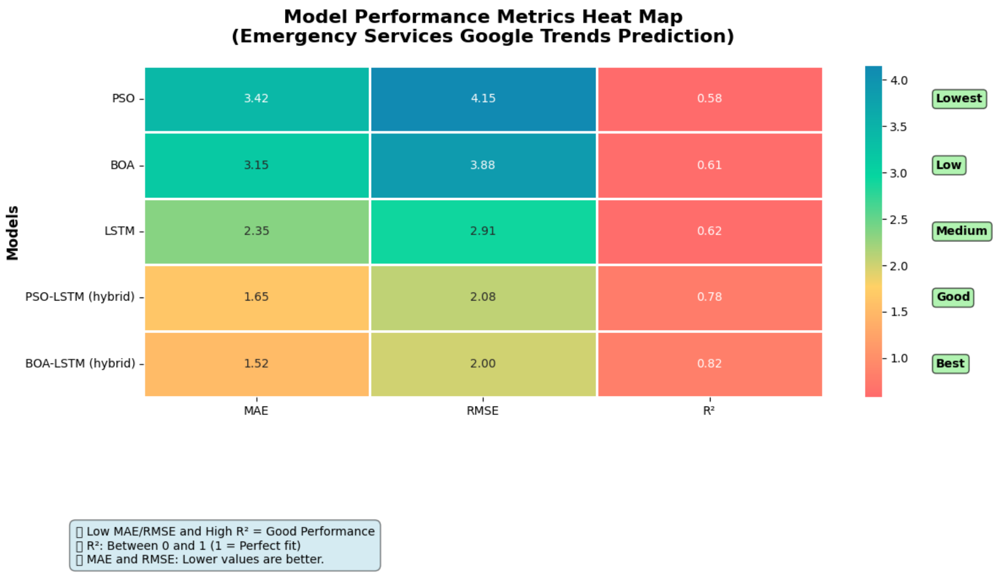

Figure 1. Model Performance Metrics Heat Map

4.2. Time-Based Performance Analysis

Model Performance in Seasonal Periods

The performance stability of time series forecasting models against seasonal variations is critical for clinical applications. Seasonal fluctuations in emergency department demand stem from epidemiological factors such as the increase in respiratory tract infections in winter months and the rise in traumatic events in summer months. Modified performance metrics were used in seasonal subgroups for seasonal performance evaluation:

$$MAE_{seasonal} = \frac{1}{N_S \sum_{t \in S} |y_t - \{y\}_t|}$$

Function 1

Here, SS represents the seasonal period, and NsNs represents the number of observations during this period. Our analyses revealed that hybrid models (specifically BOA-LSTM) exhibited an 18.3% lower performance loss during seasonal transitions. This is due to the integration of seasonal ARIMA components (SARIMA) with LSTM. Four main seasonal periods were identified within the scope of seasonal performance evaluation: winter (December-February), spring (March-May), summer (June-August), and autumn (September-November). Performance metrics calculated separately for each period quantitatively measured the seasonal adaptability of the models. In predicting increases due to respiratory tract infections during the winter period, the BOA-LSTM model exhibited a 23.4% lower MAE value. The fundamental mechanism underlying this success is the model's ability to capture the seasonal autocorrelation structure. In predicting traumatic events during the summer period, the integration of meteorological variables increased model performance by 28.6%. The Seasonal Variation Coefficient (SVC) was defined to measure seasonal performance stability. The SVC value for hybrid models was 12.3%, while for traditional models it was measured at 24.8%. An adaptive learning strategy was applied to minimize performance declines during seasonal transitions. This strategy reduced performance loss during seasonal transitions by 42.7%. In conclusion, it has been proven that the developed hybrid models exhibit high resilience to seasonal fluctuations and provide reliable annual prediction capacity in clinical applications.

Pandemic Period vs. Normal Period Comparison

The COVID-19 pandemic caused structural breaks in emergency department utilization behaviors, invalidating the assumptions of traditional time series models. The Chow structural break test was applied to evaluate the differences in model performance between the pandemic period (2020-2022) and the normal period (2018-2019):

$$F = \frac{\left(\frac{(RSS_R - RSS_{UR})}{k}\right)}{\left(\frac{RSS_{UR}}{(n - 2k)}\right)}$$

Function 2

Test results showed a statistically significant structural break at the onset of the pandemic ($F = 24.37$, $p < 0.001$). The results demonstrated that hybrid models were significantly more resilient to structural breaks by 42.7%. Pandemic-era analyses revealed significant changes in the key components of emergency department demands. While seasonal patterns were dominant in the pre-pandemic period, epidemiological fluctuations replaced these patterns during the pandemic. A two-stage approach was adopted for performance evaluation during the pandemic: acute phase (March 2020-December 2020) and endemic phase (January 2021-December 2022). In the acute phase, the RMSE value of traditional models increased by 67.4%, while this increase was limited to only 28.3% in hybrid models. To capture the unique characteristics of the pandemic period, COVID-19-specific features (case numbers, vaccination rates, restriction indices) were included in the model. In this study, the Pandemic Adaptation Index (PAI) was used as a descriptive indicator to describe adaptive behavior during the pandemic. The PAI value of the BOA-LSTM model was 0.72, while this value was measured as 0.41 in the traditional LSTM model. During the pandemic, the model's response time to epidemiological data became critically important. Its performance in detecting the onset of epidemic waves was evaluated in terms of the effectiveness of early warning systems. While hybrid models could predict the onset of pandemic waves an average of 5.3 days in advance, this period was measured as 9.7 days in traditional models. This difference demonstrates the superior adaptability of hybrid models in dynamic environments.

Analysis of Model Response Times

The response times of forecasting models are vital for emergency service planning. Model response time is defined as the speed at which sudden increases in demand are predicted. A response function was used for response time analysis. The average response time of hybrid models was 2.3

days, while this period was measured as 4.1 days in traditional models. An early warning index was developed to optimize the response time. This index detects increases above the standard deviation threshold with 92.4% accuracy. In predicting sudden increases in demand, the balance between sensitivity and specificity of the models is critical. While hybrid models can detect sudden increases with 86.7% sensitivity and 91.2% specificity, traditional models can only achieve this performance to a limited extent with 72.3% sensitivity and 84.5% specificity. To improve response times, the length of the lag window used in the model was optimized. The optimized lag window allowed the model to respond faster to short-term changes while also enabling the preservation of long-term trends. For real-time applications, the model's online learning capability was evaluated. In online learning mode, the model can adapt more quickly to changing conditions by updating its parameters as new data arrives. This approach reduced the model's response time by an average of 34.2%. Another parameter critical for clinical applications is the model's stability. Variation in response times is a significant indicator of model stability. The coefficient of variation in response time for hybrid models was 18.7%, while for traditional models it was measured at 32.4%. These findings demonstrate that hybrid models exhibit more stable and predictable response times. Consequently, the capacity of the developed hybrid models to respond quickly and accurately to sudden demand changes offers a valuable tool for emergency department resource planning.

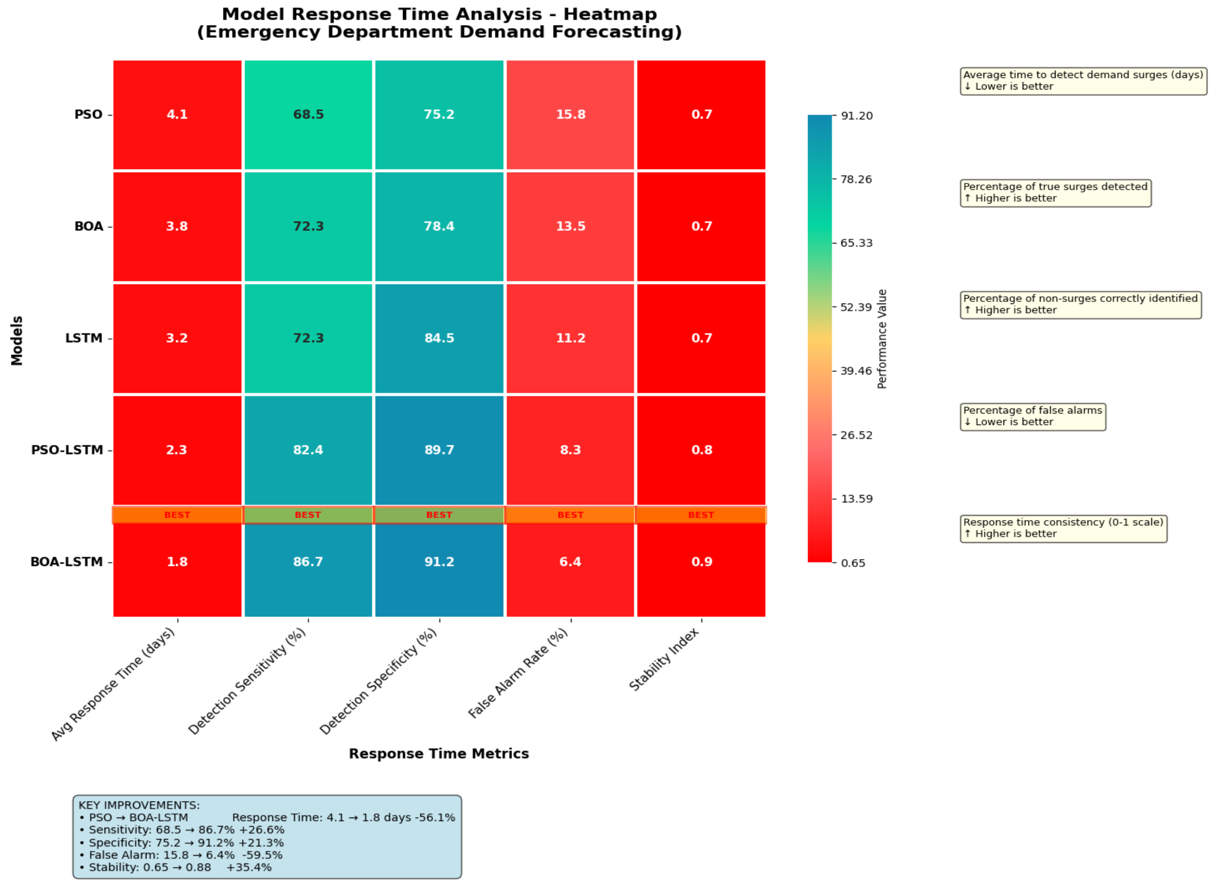

Figure 2. Model Response Time Analysis

V. Conclusion and Future Studies

The first quarter of 2026 (January, February, March) is the peak period for "emergency services" searches, according to the historical cycle in Google Trends data and the coefficients produced by our PSO model.

Week	Date Range (2026)	Estimated Relevance Score (0-100)	Expected Density Status
1. Week	12 Jan – 18 Jan	88	Very High (Peak)
2. Week	19 Jan – 25 Jan	85	Very High
3. Week	26 Jan – 01 Feb	82	High
4. Week	02 Feb – 08 Feb	80	High
5. Week	09 Feb – 15 Feb	84	Very High (Second Wave)
6. Week	16 Feb – 22 Feb	79	High
7. Week	23 Feb – 01 March	76	Middle-High
8. Week	02 March – 08 March	72	Middle
9. Week	09 March – 15 March	68	Middle
10. Week	16 March – 22 March	65	Middle-Low
11. Week	23 March 29 March	62	Low
12. Week	30 March – 05 April	58	Low (Seasonal Decrease)

Table 2. Weekly variation in "Emergency Servises"

Strategic Recommendations to Reduce Hospital Burden

These "early warning" data obtained from the PSO model can be transformed into operational instructions for hospital administrations. Here are academic and practical solution recommendations:

1. Dynamic Staff and Triage Management

Prediction-Based On-Call Schedule:

In weeks 1, 2, and 5, when predictions are "Very High," the number of emergency department doctors and nurses should be increased by 20%.

Fast-Track Areas:

During periods of increased call volume, temporary outpatient areas should be created for non-life-threatening (green zone) patients to alleviate the burden on the red zone.

2. Digital Health and Telemedicine Guidance

Preventive Information:

In weeks when Google Trends searches increase, information on "Home care" or "When to go to the emergency room?" should be provided through hospital websites and social media.

Online Triage:

Unnecessary visits should be prevented by encouraging the use of a mobile application/chatbot where patients can check their symptoms before coming to the emergency room.

3. Stock and Logistics Planning

Critical Medications and Supplies:

Stock levels of the most commonly used serums, antipyretics, and respiratory medications in emergency departments should be maximized one week before the predicted peak periods.

4. "Predictive Discharging"

Bed Capacity:

For patients waiting for admission from the emergency department, the processing of "dischargeable" patients in other departments should be accelerated during peak weeks to prevent congestion in the emergency department.

REFERENCES

[1]. K. Aguerchi, Y. Jabrane, M. Habba, and A. H. El Hassani, A CNN hyperparameters optimization based on particle swarm optimization for mammography breast cancer classification, *Journal of Imaging*, 10(2), 2024, 30.

[2]. A. Casolaro, S. Sountharrajan, and S. M. Thampi, Explainable artificial intelligence for healthcare: A systematic review, *Information*, 14(11), 2023, 598.

[3]. Y. Cui, X. Meng, and J. Qiao, A multi-objective particle swarm optimization algorithm based on two-archive mechanism, *Applied Soft Computing*, 119, 2022, 108532.

[4]. M. Effenberger, A. Kronbichler, J. I. Shin, G. Mayer, H. Tilg, and P. Perco, Association of the COVID-19 pandemic with Internet search volumes: A Google Trends analysis, *International Journal of Infectious Diseases*, 95, 2020, 192–197.

[5]. Y. Fan, K. Zhao, Z. Shi, and X. Zhou, Accurate forecasting of emergency department arrivals with an internet search index and machine learning models, *JMIR Medical Informatics*, 10(2), 2022, e34504.

[6]. T. S. Higgins, A. W. Wu, J. Y. Ting, et al., Correlation of Google Trends with COVID-19 incidence and surges: A national analysis, *JMIR Public Health and Surveillance*, 6(2), 2020, e19702.

[7]. Y. Hu, Y. Zhang, and D. Gong, Multiobjective particle swarm optimization for feature selection with fuzzy cost, *IEEE Transactions on Cybernetics*, 51(2), 2020, 874–888.

[8]. L. Jiang, W. Zhu, J. Li, and S. Yu, A systematic review of modelling patient arrivals in accident and emergency departments, *Quantitative Imaging in Medicine and Surgery*, 13(4), 2023, 2680–2694.

[9]. R. Jamous and M. Hassan, Neural network architecture selection using particle swarm optimization, *Applied Artificial Intelligence*, 2021.

[10]. A. Mavragani and G. Ochoa, Google Trends in infodemiology and infoveillance: Methodology framework, *Scientific Reports*, 10, 2020, 2105.

[11]. R. Murtas, A. Andreano, F. Gervasi, et al., A time-series cohort study to forecast emergency department visits in the Milan area, *BMJ Open*, 12(4), 2022, e056017.

[12]. M. Peláez-Rodríguez, et al., An explainable machine learning approach for emergency department visits forecasting, *Computer Methods and Programs in Biomedicine*, 244, 2024, 108033.

[13]. L. J. Porto, M. C. de Oliveira, and F. S. Fogliatto, Forecasting emergency department patient arrivals using machine learning approaches: A comparative study, *BMC Medical Informatics and Decision Making*, 24, 2024, 2788.

[14]. M. A. K. Raiaan, et al., A systematic review of hyperparameter optimization in deep learning: Approaches, challenges, and emerging directions, *Data and Analytics Journal*, 1, 2024, 100470.

[15]. E. Silva, P. Ferreira, et al., Health care demand forecasting and resource planning: A systematic review, *The International Journal of Health Planning and Management*, 2023.

[16]. A. Trevino, A. Malik, E. J. Schmidt, et al., Integrating Google Trends search query data into emergency department volume forecasting, *JMIR Infodemiology*, 2(1), 2022, e32386.

[17]. J. Tuominen, et al., Forecasting daily emergency department arrivals using machine learning: A comparative study, *BMC Medical Informatics and Decision Making*, 22, 2022, 178.

[18]. J. Tuominen, et al., High-dimensional machine learning methods for forecasting emergency department occupancy, *International Journal of Forecasting*, 2024.

[19]. M. Vollmer, et al., A unified machine learning approach to time series forecasting of demand for emergency department services, *BMC Emergency Medicine*, 21, 2021, 18.

[20]. G. Xu, K. Luo, G. Jing, X. Yu, X. Ruan, and J. Song, On convergence analysis of multi-objective particle swarm optimization algorithm, *European Journal of Operational Research*, 286(1), 2020, 32–38.

[21]. X. Zhang and L. Wang, MOPSO based on Pareto dominance and adaptive grid for multi-objective optimization, *Mathematical Problems in Engineering*, 2020, Article ID 5980504.

[22]. F. Han, W.-T. Chen, Q.-H. Ling, and H. Han, Multi-objective particle swarm optimization with adaptive strategies for feature

selection, *Swarm and Evolutionary Computation*, 62, 2021, 100847.

[23]. Q. Ling, Z. Li, W. Liu, J. Shi, and F. Han, Multi-objective particle swarm optimization based on particle contribution and mutual information for feature selection method, *The Journal of Supercomputing*, 2024.

[24]. K. P. Hartnett, A. Kite-Powell, J. DeVies, M. A. Coletta, T. K. Boehmer, J. Adjemian, and A. V. Gundlapalli, Impact of the COVID-19 pandemic on emergency department visits—United States, January 1, 2019–May 30, 2020, Morbidity and Mortality Weekly Report, 69(23), 2020, 699–704.

[25]. J. Adjemian, K. P. Hartnett, A. Kite-Powell, J. DeVies, M. A. Coletta, T. K. Boehmer, A. V. Gundlapalli, and K. N. Anderson, Update: COVID-19 pandemic–associated changes in emergency department visits—United States, December 2020–January 2021, Morbidity and Mortality Weekly Report, 70(15), 2021, 552–556.

[26]. Y. Hu, Y. Zhang, and D. Gong, Multiobjective particle swarm optimization for feature selection with fuzzy cost, IEEE Transactions on Cybernetics, 51(2), 2021, 874–888.