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A Novel Hybrid Approach for Daily Tourism Arrival Forecasting: The PROPHET-Bayesian Gaussian Process-Forward Neural Network Model

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ABSTRACT

In light of the profound impact of the COVID-19 pandemic on the tourism sector, accurate forecasting of daily visitor arrivals has become paramount. Introduced herein is a novel PROPHET-Bayesian Gaussian Process-Forward Neural Network (PROPHET-BGP-FNN) model, an advanced deep learning (DL) approach, devised for this purpose. This model uniquely integrates the PROPHET model with a deep neural network, merging BGP and FNN, thereby enabling the detection of both linear and nonlinear data attributes. Linear characteristics are discerned by the PROPHET component. Contrary to traditional methodologies which predominantly employ monthly or quarterly datasets, this approach harnesses the precision of daily data, thereby offering a timely and refined forecast. Given the complexity of daily tourist demand data, which manifests a blend of linear and nonlinear patterns, the conventional frameworks often fall short in representation. Through an application on Hawaiian tourism data spanning 2017 to 2021, 80% of which was employed for training and the remainder for validation, it was observed that the PROPHET-BGP-FNN model surpassed benchmark models, including Long Short-Term Memory (LSTM)-SARIMAX-PROPHET, with a remarkable forecast accuracy of 97%. This investigation underscores the viability of integrating high-frequency data with cutting-edge machine learning (ML) methodologies for a more precise forecast in tourism demand. Such insights hold significant implications for strategic decision-making, thereby enhancing the tourism sector's economic viability and competitive stance.

1. INTRODUCTION

Tourism has been identified as a major contributor to the economic advancement of numerous nations. Substantial research has been dedicated to forecasting tourism demand [1]. In particular, tourism serves as a cornerstone for Hawaii's economy. State government statistics revealed that the Hawaiian Islands were visited by more than 6.4 million visitors in 2003, with expenditures surpassing 10 billion dollars [2]. The dominant markets from which these visitors hailed included the United States of America (West and East), Japan, and Canada.

However, 2020 witnessed a drastic alteration in the global tourism landscape. The emergence of the COVID-19 epidemic profoundly affected Hawaii's tourism sector. Hawaii's initial case was reported in March 2020 [3]. Subsequently, the World Health Organization (WHO) categorized the outbreak of the novel coronavirus (2019-nCoV) as a global pandemic on March 6, 2020. Classified as a severe acute respiratory syndrome (SARS) variant, the coronavirus (COVID-19) was declared a pandemic by the WHO, underscoring its grave nature. The inaugural case was identified in December 2019 in Wuhan, China, as a novel viral pneumonia began affecting a cluster of patients. Following its identification, various precautionary measures were employed by governments globally to curb its proliferation. These measures encompassed containment strategies, prompt testing, mandatory mask usage, self-isolation, and the enforcement of social distancing. Notably, the countries most impacted encompassed the United States, India, Brazil, France, Germany, the United Kingdom, Russia, South Korea, Italy, Turkey, Spain, and Vietnam [4]. Global travel restrictions and lockdowns were imposed by January 2020 to thwart the spread of the SARS-CoV-2 virus, inducing a palpable shockwave through the global tourism and hospitality sectors. Such reverberations were profoundly felt in tourism-centric economies. In stark contrast to previous years, 2019's data showcased a plummet in Hawaiian tourist arrivals by 73.9%, resulting in a mere 2,708,258 visitors. Arrivals by air and cruise ship saw reductions by 73.9% (2,678,073 individuals) and 79.0% (30,185 guests) respectively. Consequently, the cumulative visitor days witnessed a 68.3% decline [2, 5].

The incorporation of Artificial Intelligence (AI) in predicting tourist arrivals is increasingly recognized as a revolutionary approach to a complex predicament. AI has been demonstrated to possess superior aptitude in deciphering intricate data patterns, discerning nonlinear relationships, and identifying dynamic shifts. The urgency to integrate AI into tourism forecasting is emphasized by its potential to amplify the precision and flexibility of predictions, notably in tumultuous periods exemplified by the COVID-19 outbreak. Nevertheless, such incorporations are not devoid of hurdles. Conventional forecasting techniques often wrestle with the intricacies presented by high-frequency data and multifaceted patterns. The pandemic's pronounced disruptions have illuminated these predicaments, necessitating a profound reevaluation and recalibration of prediction models. This retooling is imperative to encapsulate rapid alterations in tourist behaviors, governance protocols, and health stipulations. Leveraging AI emerges as a prospective pathway to traverse these multifaceted challenges. Harnessing the power of AI facilitates a nuanced extraction of insights from expansive and variegated data pools, ultimately culminating in a more refined and adaptive forecasting strategy, especially amidst global uncertainties akin to the COVID-19 scenario.

DL has been extensively employed for predictive tasks, offering advancements over traditional AI models. Notably, most extant research has been oriented towards quarterly or monthly data, which, due to their low frequency, might provide limited insights. In contrast, daily data, given its higher frequency, is posited to furnish richer information. It has been confirmed by researchers that oscillations in tourist arrivals can be categorized into trends, irregularities, or seasonal components [6]. The complexity of forecasting daily tourist arrivals arises from the intricate interplay of linear trends and nonlinear patterns.

Predominantly, scholarly efforts have focused on leveraging diverse quantitative techniques, such as time series, econometrics, and AI, to forecast the volume of international visitors [6]. Within the domain of AI, neural network models have been discerned as potent tools for the tourism industry. It is acknowledged that DL falls under the umbrella of ML, which subsequently is a subset of AI. A salient feature distinguishing DL models from traditional neural networks is the heightened complexity, particularly in the depth of hidden layers within the neural architecture. In light of the COVID-19 pandemic's profound disruption of the tourism sector, there arises an imperative to estimate tourist flows using available pandemic-related data in tandem with inbound tourist statistics. A multitude of researchers and data scientists are engaged in the development of predictive models, aiming to elucidate the potential trajectory of the virus, which could serve to better forecast its proliferation [1].

Historically, the prowess of DL has been manifested in its adept handling of intricate data sets, exemplified in diverse studies such as face verification [7], Bitcoin price forecasting [8], and facial recognition [9]. This efficacy is largely attributed to DL's capability to autonomously discern and extract distinguishing features, obviating the necessity for extensive manual intervention or domain-specific knowledge. Yet, it is posited that solely relying on DL for forecasting tourist arrivals might be suboptimal, given the multifaceted nature of tourist arrival data. While Artificial Neural Networks (ANNs) are theoretically capable of modeling any nonlinear function with remarkable precision, they often encounter the pitfall of overfitting, leading to suboptimal performance. In this context, hybrid models emerge as promising solutions. Travel restrictions instituted in response to the COVID-19 pandemic have undeniably reshaped global tourism trends. Given the perceived superiority of daily data over lower-frequency data, daily tourist arrival statistics have been harnessed to craft daily forecasts. Consequently, a paramount research query is the development of a hybrid model that adeptly leverages time series data to refine the accuracy of tourist arrival predictions during the COVID-19 era. In addressing this, a linear technique amalgamated with nonlinear methodologies (PROPHET-BGP-FNN) is proposed. Challenges arise from mixed patterns in the data; while linear models often falter in modeling nonlinear patterns, their nonlinear counterparts are similarly encumbered when faced with linear patterns. This underscores the intricacy of effectively navigating data patterns that are interspersed with both linear and nonlinear elements. Notably, the trajectory of research in tourism prediction has seen the integration of time-series algorithms with both conventional neural network strategies and advanced DL methodologies.

In a comparative study conducted by Bouhaddour et al. [10], the SARIMA and PROPHET prediction models were evaluated for their capacity to forecast tourism in Singapore. These evaluations were based on historical tourist arrival data. While SARIMA is recognized for its proficiency in delineating both seasonal and non-seasonal patterns, the PROPHET model encompasses trend alterations and seasonality. Comparative metrics, such as mean absolute error (MSE) and root mean squared error (RMSE), were employed to gauge the forecasting performance. It was found that the PROPHET model exhibited superior forecasting capabilities compared to SARIMA. These findings hold significance, offering pertinent insights for refining tourism demand predictions, thereby aiding policymakers and industry stakeholders in their decision-making pursuits.

A distinct research endeavor led by Alamsyah et al. [11] delved into the application of ANN models for prognosticating tourism demand in Indonesia. The overarching objective was to augment the precision of tourism demand forecasts by harnessing the innate ability of ANNs to discern intricate patterns and nonlinear associations. Historical tourism data from Indonesia was utilized for training and assessment of the ANN models. Performance metrics such as mean absolute percentage error (MAPE) and RMSE were adopted to ascertain forecast accuracy. It was inferred that ANN models demonstrated commendable efficacy in prognosticating tourism demand, imparting valuable insights for strategic tourism planning in I MAPE Indonesia.

Wu et al. [12] proffered a novel forecasting methodology, amalgamating seasonal auto-regressive integrated moving average (SARIMA) with LSTM. This innovative approach was tailored for the prompt prediction of daily tourist arrivals in Macau SAR, China. LSTM, being a nonlinear AI methodology, is adept at encapsulating long-term contingencies in time series data. By synergizing the predictive prowess of SARIMA with LSTM's proficiency in residual reduction, the combined SARIMA + LSTM model was observed to eclipse other predictive techniques in efficacy. This research augments best practices in the tourism industry, particularly in terms of achieving precise daily arrival predictions.

Furthering the discourse, Assaf et al. [13] incorporated the Bayesian Global Vector Autoregressive (BGVAR) model for the formulation and prediction of regional tourism demand. The BGVAR framework integrates Bayesian statistical tenets and effectively captures interdependencies spanning multiple variables within a vector autoregressive (VAR) model. The deployment of the BGVAR model for regional tourism demand was undertaken with the intent to refine the accuracy and reliability of predictions.

Collectively, these studies underscore the continuous evolution and diversity of methods employed in tourism forecasting. Such advancements not only pave the way for enhanced predictive accuracy but also facilitate informed decision-making processes within the tourism industry.

In the extensive review of literature concerning proxies capturing tourism demand, the number of tourist arrivals was identified as the predominant variable employed. The discourse encompassed three principal methodologies utilized in the realm of tourist demand forecasting: econometrics, time series, and AI-based techniques. Nevertheless, in the present study, a composite model is introduced for forecasting tourist arrivals in Hawaii. Given that the time series of tourist arrivals manifests both linear and nonlinear characteristics, a composite prediction model, PROPHET -BGP-FNN, was constructed by integrating the PROPHET model, known for its adeptness at learning long-term historical data characteristics [14]. This hybrid model seeks to harness the advantages of the PROPHET model while preserving the predictive capabilities inherent to FNN-BGP models.

The impetus for this research has been shaped by the pressing demand for robust and adaptable forecasting instruments tailored for the tourism sector, especially in prominent destinations such as Hawaii. This urgency has been exacerbated by unforeseen disruptions, notably the COVID-19 pandemic. The envisaged practical ramifications of this research echo profoundly within the industry's recuperative endeavors. The composite forecasting model, PROPHET-BGP-FNN, is posited to equip stakeholders with an instrumental tool adept at anticipating the intricate vicissitudes in daily tourist arrivals. The pivotal applicability of this study is perceived in its prospective contributions to reinvigorating the tourism domain, accentuating its adaptability and resilience during periods characterized by flux and unpredictability.

Moreover, the efficacy of the PROPHET-BGP-FNN model in estimating the count of tourist arrivals is evaluated by contrasting its performance against that of four distinct models, notably SARIMAX, LSTM, and PROPHET.

The ensuing manuscript is systematically organized. Section 2 elucidates the methodology underpinning the proposed PROPHET-BGP-FNN model, supplemented by foundational knowledge. Section 3 delineates the process of data preparation, the model's implementation, and an analytical exploration of the empirical results garnered. Conclusions are drawn in Section 4.

2. METHODOLOGY

2.1 Traditional prediction models

2.1.1 LSTM model

LSTM is identified as a variant of the recurrent neural network (RNN) architecture, formulated to address the intricacies of sequential data patterns. Contrary to conventional RNNs, the structure of LSTMs has been reported to counteract the vanishing gradient dilemma, allowing for the efficient retention and learning from extended sequences' dependencies [6]. Such proficiency is attributed to their specialized memory cell configuration, outfitted with distinct gates, namely input, forget, and output, which orchestrate the progression of information. These gates facilitate the LSTM's capacity to selectively conserve pertinent information across protracted intervals, and subsequently to generate accurate predictions or classifications across diverse realms, including natural language processing, speech recognition, and time series analysis [15]. Memory cells in LSTMs, integrated with these gate mechanisms, dictate the learning trajectory by discerning the information to be retained, omitted, or relayed [9]. Though acknowledged for their adeptness in deciphering sophisticated sequential patterns apt for time series analysis, LSTMs have been observed to grapple with impediments such as the vanishing gradient phenomenon during training. Such constraints could potentially undermine their efficacy in discerning prolonged sequence associations. The PROPHET-BGP-FNN model is postulated to augment this by synergizing DL's prowess with Bayesian optimization, thereby amplifying the model's capability to discern both short and long-term sequence intricacies.

2.1.2 SARIMAX (SARIMA with eXogenous Factors) model

The SARIMAX model has been delineated as an advanced time series forecasting construct that broadens the conventional ARIMA model, facilitating the inclusion of seasonal components and exogenous variables. It has been demonstrated to discern patterns in time series datasets by emphasizing autoregressive (AR) and moving average (MA) components [9]. Concurrently, differencing is employed to ensure data stationarity. Furthermore, its framework encompasses the effects of seasonality through designated seasonal AR and MA terms. A distinctive feature of SARIMAX is its ability to assimilate exogenous regressors, thereby empowering the model to integrate external determinants influencing the behavior of time series data. Such versatility has rendered SARIMAX especially advantageous for forecasting tasks in which external variables critically impact observed data patterns, such as economic indicators in sales forecasts or meteorological data in energy demand predictions [10, 12]. Despite SARIMAX's strength as a comprehensive model adept at integrating seasonality and exogenous components, it has been noted to exhibit limitations when confronted with intricate, non-linear patterns frequently found in tourism datasets. Inherent assumptions of linearity and stationarity might not be optimal for modeling nuanced interactions within certain data sets. The PROPHET-BGP-FNN model endeavors to redress these constraints by tapping into the non-linear potentials of DL combined with BGP, optimizing the extraction of both linear and non-linear data facets.

In essence, both LSTM and SARIMAX, while pivotal in the domain of time series analysis, manifest discernible vulnerabilities, particularly in delineating multifaceted patterns and non-linear data relationships. The PROPHET-BGP-FNN model emerges as a remedy, fusing DL, Bayesian optimization, and probabilistic modeling, thereby fostering a holistic forecasting paradigm aptly tailored for the intricacies characteristic of tourism demand data.

2.2 The PROPHET-BGP-FNN prediction model

2.2.1 Neural PROPHET model

The foundation of Neural PROPHET is laid upon the Python and R-based model " PROPHET ", which has been documented for its utility in forecasting time series data [14]. A significant concept introduced by the Neural PROPHET model is modular composability, thereby amplifying its adaptability and versatility [15]. This model is constructed with discrete modules, each of which contributes an additive element to the forecast. Additionally, by scaling with the trend, numerous components can be adjusted to possess a multiplicative effect. Despite each module functioning with distinct inputs and modeling processes, it is mandated that they yield z outputs, where h symbolizes the consecutive future steps predicted. These prognostications, denoted as $\hat{z},\ldots,\hat{z}_{t+h-1}$, correspond to impending values of the time series $z_t, \ldots, z_{t+h-1}$. In instances where dependency is solely time-based, an arbitrary number of forecasts can be generated. From a mathematical perspective, this specific scenario is equated to a one-step ahead prediction with z=1.

$$\hat{z}_t = T(t) + S(t) + E(T) + F(t) + A(t) + L(t) \qquad (1)$$

where,

T(t) signifies the trend at time t;

S(t) stands for seasonal effects at time t;

E(t) represents event and holiday impacts at time t;

F(t) corresponds to regression effects at time t for upcoming-known exogenous variables;

A(t) indicates auto-regression effects at time t based on prior observations;

L(t) delineates regression effects at time t for lagged observations of exogenous variables.

To architect the model, individual component modules might be adjusted and amalgamated in isolation:

Trend T(t): Within the Neural PROPHET model, the trend component encapsulates the overall trajectory and direction of time series data. Both linear and non-linear functions have been employed to depict the trend, thereby accommodating different trend patterns. The trend's essence, established by merging an offset (m) with a growth rate (k), has been traditionally recognized. The trend's influence at a distinct time (t_1) is deduced by magnifying the growth rate with the elapsed time from the trend's initiation (t_0), supplemented by the offset (m).

$$T(t_1)=m+k.(t_1-t_0) \qquad (2)$$

Seasonality S(t): Seasonality is characterized by repetitive patterns manifesting at consistent intervals within data. By integrating seasonal components, such as yearly or weekly seasonality, the PROPHET model captures these repetitive nuances. Through the employment of Fourier terms, the management of seasonality in Neural PROPHET has been facilitated [16]. For each designated seasonality, a predetermined number of Fourier terms are instituted, as portrayed in Eq. (3), wherein k is the number of Fourier terms earmarked for the seasonality with periodicity p.

$$S(t) = \sum_{j=1}^{k} \left(a_j.\cos\frac{2\pi jt}{p} + b_j.\sin\frac{2\pi jt}{p}\right) \qquad (3)$$

Holidays E(t): Special events or holidays can induce marked variations in time series data. A holiday component has been embedded in the PROPHET model to encapsulate the ramifications of such occurrences. This inclusion enables the pinpointing of specific dates or durations tied to holidays, allowing for their potential impact on the dataset to be considered. By acknowledging holiday effects, predictions can more adeptly capture anomalies arising during such intervals.

The PROPHET model's versatility enables its classification both as a linear and non-linear construct, contingent upon its application and integral components. The overarching trend in time series data is captured through a linear regression model employed by PROPHET. Nonetheless, PROPHET also assimilates various non-linear elements, inclusive of seasonality and holiday implications, facilitating the depiction of intricate data patterns that might elude a rudimentary linear regression model. In essence, PROPHET emerges as a hybrid model, amalgamating both linear and non-linear methodologies. The integration of both linear and non-linear components equips PROPHET to comprehend an extensive gamut of intricate patterns within time series data, solidifying its stature as a formidable forecasting tool.

2.2.2 The FNN model

An FNN, as depicted in Figure 1, represents a foundational architecture within the realm of neural networks. This model encompasses several layers: an input layer designed for data reception, one or multiple hidden layers dedicated to processing and discerning patterns, and an output layer tasked with rendering predictions. Within these layers, neurons are interconnected through weights and biases. Data is transmitted through the network by these weighted connections, and, in the hidden layers, activation functions are applied to encapsulate nonlinear associations. The culmination of this process, known as forward propagation, yields the final output. Using labeled data alongside a loss function, the FNN undergoes training, wherein the adjustment of weights and biases is carried out to curtail prediction discrepancies. This model serves as the bedrock upon which more intricate neural network configurations are based, making it indispensable for activities like classification and regression. Notably, in recent times, the FNN has been recognized for its DL-based time series forecasting capacities, especially its prowess in delineating intricate temporal links within datasets. Within the sphere of tourism demand forecasting, this model has been employed to decipher the nuanced interconnections amongst myriad tourism demand determinants and to prognosticate forthcoming demand levels with precision [17, 18]. However, the quest for discerning the optimal set of hyperparameters for an FNN model has been identified as a process that can be arduous, resource-intensive, and computationally demanding [19].

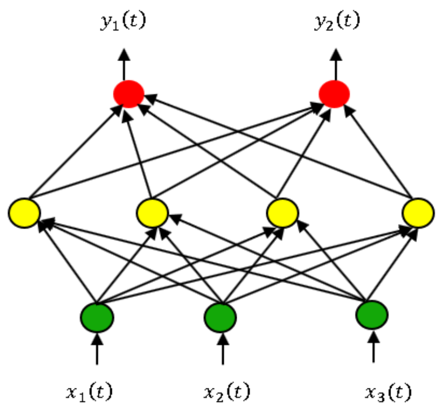

Figure 1. Depiction of a fully connected layered feed-FNN with a singular hidden layer. Neurons in the input layer are represented in green, outputs in red, and hidden neurons are illustrated in yellow

2.2.3 BGP model

BGP optimization is characterized as a methodology for the optimization of black-box functions. In instances where the analytical form of the function remains elusive, evaluations at specific data points can still be conducted. A notable attribute of the BGP is its proficiency in modeling intricate non-linear functions and discerning correlations amongst input variables. This model is delineated by a mean function and a covariance function, each elucidating the prior distribution over the functional space. The mean function denotes the anticipated value of the function, whereas the covariance function encapsulates the correlation magnitude between the input variables. By synergizing these models, both deterministic and stochastic facets of the time series were captured, leading to enhanced predictive accuracy [20].

For hyperparameter tuning within ML realms, the prowess of the BGP becomes evident. It demonstrates marked utility, especially when confronted with multifaceted models brimming with hyperparameters demanding calibration. An exemplar pseudo-code for Bayesian optimization is provided in Figure 2.

The foundational step of the algorithm entails establishing a prior distribution over the objective function, emblematic of the preliminary beliefs regarding the function, pre-observations. Subsequently, with each iteration, hyperparameters for evaluation are chosen in line with the acquisition function. This function optimally melds exploration with exploitation, earmarking the point characterized by the paramount expected enhancement in objective function value. Post this evaluation, the Gaussian process undergoes an update with the newly procured observation, and the procedure is iteratively repeated until an agreeable solution emerges. A salient advantage of Gaussian process-based optimization resides in its capability to manage noisy objectives that are resource-intensive to evaluate. Moreover, it extends a probabilistic framework conducive to uncertainty quantification and adaptive exploration. The algorithmic structure for Bayesian optimization is detailed as follows [20]:

Algorithm 1 Pseudo-Code for Bayesian Optimization

A Gaussian process prior is placed on f.
At n_0 points, f is observed pursuant to an initial space-filling experimental design. Here, n is set as $n=n_0$.
while n remains $\leq N$:
The posterior probability distribution on f is updated using accessible data.
x_n is defined as the acquisition function's maximizer over x, computed utilizing the prevailing posterior distribution.
An observation is made: $y_n=f(x_n)$.
Increment n
end while
The concluding solution is returned: either the data point assessed with the supreme $f(x)$ or the point epitomized by the most substantial posterior mean.

2.2.4 BGP-FNN model

The efficacy of the BGP-FNN model in modeling residuals, often elusive to traditional time series models, has been observed. By merging these methodologies, not only are the inherent strengths of both models harnessed, but a resilient framework for the quantification of uncertainty in predictions is also established. Bayesian optimization, rooted in probabilistic modeling of the function, identifies the subsequent evaluation point based on estimated performance. Iterative updates to the model with fresh evaluations aim to discern the optimal set of hyperparameters, enhancing the target performance metric. An efficient, automated exploration of the hyperparameter space is facilitated by Bayesian optimization, its objective being the identification of the most proficient configuration that amplifies metrics like accuracy.

Upon integration with the FNN model, an avenue for pinpointing the pinnacle hyperparameters that boost the model's performance is paved. BGP-FNN models, representative of DL architectures, possess the capacity to concurrently process spatial and temporal attributes in sequence data. Nonetheless, the triumph of these models is intricately linked to hyperparameter selection, encompassing elements like learning rate, batch size, convolutional layer count, dropout rate, and regularization intensity. It has been observed that employing BGP-FNN enhances performance and generalization, curtails overfitting, and conserves resources in contrast to manual hyperparameter adjustments.

For the task of identifying both spatial relations and temporal dependencies in time series data, the BGP-FNN model is utilized. The unique nonlinear patterns discerned become instrumental in modeling the residual sequence of the model in question. The capability of BGP-FNN model networks to assimilate spatial and temporal characteristics in a data sequence has been emphasized. A plethora of hyperparameters, including the count of convolutional filters, kernel dimensions, and learning rate, can be modulated to optimize the BGP-FNN model's performance. To automate the search for these hyperparameters' optimal values, Bayesian optimization can be deployed. This involves iterative evaluations of the model on a compact hyperparameter set, followed by the determination of the succeeding hyperparameter set based on prior outcomes.

2.2.5 The PROPHET-BGP-FNN model

The PROPHET-BGP-FNN model, as chosen for this study, emerges as an astute blend of disparate strengths, meticulously constructed to tackle the intricacies of forecasting tourist arrivals within time series data. This confluence of models is crafted to offer a resilient and precise predictive framework. Figure 2 delineates the operational process of the PROPHET-BGP-FNN model. The decision to employ the PROPHET-BGP-FNN model over alternative methodologies is underscored by its unique advantages. The cornerstone of this construct is the PROPHET model, recognized for its proficiency in navigating time series data laden with seasonality and trends. Concurrently, the BGP-FNN component amplifies the model's aptitude for discerning complex, non-linear patterns latent within the data. By melding these models, their individual strengths are leveraged while simultaneously instituting a robust paradigm for quantifying predictive uncertainties. As a result, both deterministic and stochastic facets of the time series are adeptly captured, culminating in heightened forecast precision. Furthermore, the incorporation of Bayesian optimization streamlines the hyperparameter optimization phase, conserving invaluable resources.

Considering the complexities inherent in tourist demand data and the paramount significance of precise arrival forecasts, the PROPHET-BGP-FNN model stands out as a formidable contender, displaying marked superiority over conventional alternatives such as SARIMAX, PROPHET, and LSTM. This avant-garde methodology adeptly navigates the subtleties of tourism forecasting, thereby bolstering the trustworthiness and accuracy of projections.

For time-series forecasting, the PROPHET-BGP-FNN model provides a robust solution characterized by enhanced precision and dependability. Over time, myriad models designed for predicting tourist demand have surfaced, encompassing econometric, time-series, or AI-driven strategies. In this instance, the PROPHET model's capabilities are merged with DL techniques, each grounded in distinct philosophical frameworks. While the PROPHET model finds frequent application in econometric scenarios, its synergy with BGP-FNN models augments its overarching efficacy. A juxtaposition of this proposed model with conventional methodologies, utilizing these dual techniques, can be assessed on multiple criteria, most notably accuracy and utility. Through the amalgamation of the PROPHET model with BGP-FNN, a potent strategy has been devised, its merit corroborated by the laudable performance metrics of MAPE and MAE.

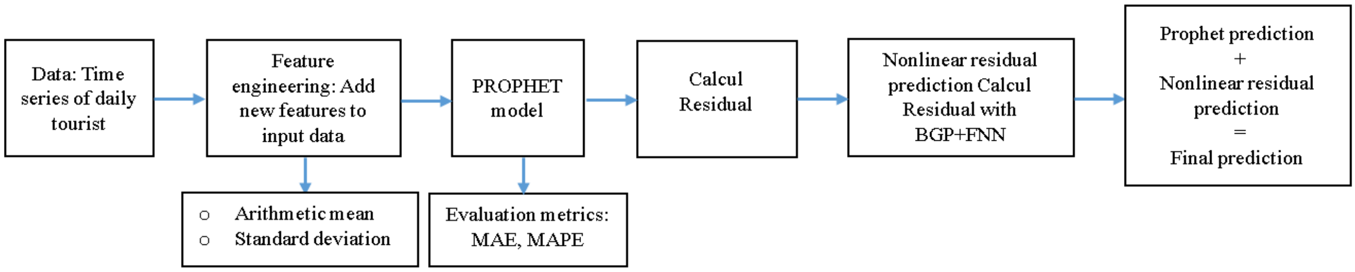

Figure 2. PROPHET-BGP-FNN-based tourist arrival time series forecasting process

3. EMPIRICAL ANALYSIS

3.1 Data preprocessing

For the purposes of this empirical investigation, real data concerning visitor arrivals were analyzed to assess the proposed model's performance. Hawaii was chosen as the subject of research due to its prominent global recognition as a leading tourist destination, experiencing consistent visitor inflows from across the world. This selection serves as a representative study for global tourism sites. Data pertaining to visitor arrivals across the four principal Hawaiian Islands was amassed for the period spanning January 1, 2017, to December 31, 2021. Figure 3 delineates the trends in visitor arrivals, and the associated descriptive statistics are encompassed in Table 1. Further insights into the flow of arrivals over this timeframe are visually represented in Figure 1, while Table 2 provides an in-depth statistical overview of the assembled dataset. Consequently, a total of 1824 observations for each origin were documented in the curated dataset.

Table 1. Descriptive statistics for daily tourist arrivals to Hawaii

	Mean	Standard Deviation
Total (Oahu+Maui+ Big Isalnd +Kauai)	23879	10740
Oahu	10332	4303
Maui	4833	2252
Big Island	2185	1070
Kauai	1599	902
From Japan	3183	2386
From Other country	1744	1196

Traditional methods were utilized to segregate the time series into discernible components for subsequent modeling. The primary components identified within the tourist demand data incorporated trends, seasonality, autocorrelation, cyclicality, and irregular patterns. These characteristics are broadly segregated into two predominant categories: a deterministic component exhibiting linear attributes and a stochastic component displaying non-linear attributes.

In the preliminary phase of this study, novel features were integrated into the dataset, aimed at enhancing the model's capacity to discern inherent patterns and interrelations. A prominent set of these incorporated features encompasses the mean and standard deviation computed over a rolling time window. These statistical attributes offer pivotal insights into data distribution, aiding the model in the identification and understanding of underlying trends and patterns. By assimilating this supplementary information, it is posited that the predictive accuracy and reliability stand to be heightened. This inclusion ensures the model's training encompasses data from both pre-pandemic and pandemic periods, facilitating a comprehensive understanding of COVID-19's impact on tourist inflows.

The engineering of features, specifically standard deviation and mean, remains a pivotal step in data analysis, as it contributes significantly to the enhancement of a model's accuracy, interpretability, and generalization. Through the extraction of these salient data attributes, deeper insights into the latent patterns and trends can be procured, thus informing decision-making based on the ensuing analyses. The data's distribution and central inclination are accurately represented by these statistics, with the standard deviation elucidating the data's variance and the mean approximating the data's central position. Typically, the derivation of standard deviation and mean proves instrumental in pinpointing potential outliers, evaluating data quality, and gleaning essential information for the modeling process. The formulae employed for the computation of mean and standard deviation are as follows:

$$\text{Arithmetic mean} = \overline{x} = \frac{\sum_{i=1}^{k} x_i}{K} \tag{4}$$

$$\text{Standard deviation} = \sqrt{\frac{1}{k-1}\sum_{i=1}^{K}(x_i - \overline{x})^2} \tag{5}$$

K: Sum of all observation.
x_i: *Observation.*

When a feature's standard deviation is observed to be significantly large, it is indicative of a pronounced variation within the data. Such variation often necessitates additional pre-processing steps to achieve normalization of the distribution. Conversely, a diminutive standard deviation intimates that the data predominantly clusters around a central value, a factor instrumental in discerning patterns and facilitating predictions. The mean of a given feature can shed light on the data's archetypal or anticipated value, which subsequently can serve as a benchmark in evaluating performance.

Subsequent to these observations, the dataset was bifurcated to facilitate empirical analyses, resulting in distinct training and validation sets.

The PROPHET model was executed on Kaggle using the Python language, targeting a span of 10 months with a daily frequency. This dataset encompasses time series data for tourist arrivals in Hawaii. Through this method, seasonal patterns and variances in tourist arrivals over the stipulated 10-month duration were captured. Opting for a daily frequency permitted a granular scrutiny of the day-to-day fluctuations in tourist activities, revealing any persistent patterns characteristic to specific days. The primary objective of this implementation was to offer a holistic view of tourist influxes to Hawaii, emphasizing seasonal trajectories, pinpointing apex travel durations, and furnishing accurate prognostications for imminent arrivals.

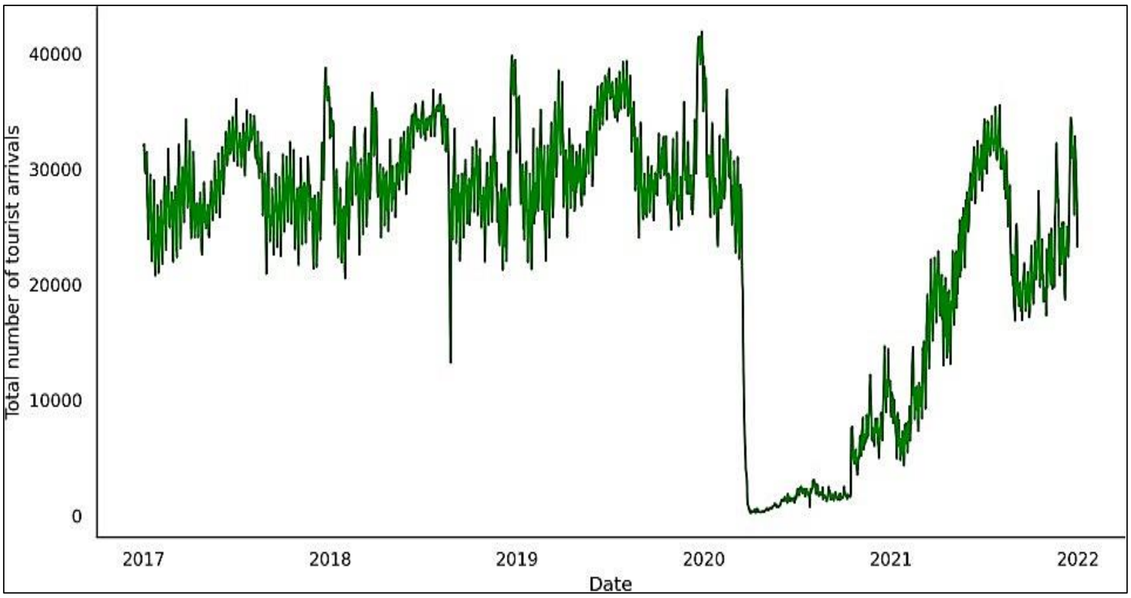

Figure 3. Cumulative tourist arrivals to the Hawaiian Archipelago

For the evaluation of the models discussed in this analysis, the metrics chosen were the Mean Absolute Error (MAE) and the MAPE. Their mathematical formulations are delineated in references [14, 21].

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{(|R_{v,i} - P_{v,i}|)}{RV} * 100 \quad (6)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\frac{(|R_{v,i} - P_{v,i}|)}{N} \quad (7)$$

N: Sum of all observation,

R_v: Reel value,

P_v: Predictive value,

The incorporation of error metrics, particularly MAE and MAPE, was deemed instrumental for a comprehensive evaluation of model performance. While MAE provides a straightforward quantification of the average discrepancies between predicted and observed values, serving as an indicator of prediction precision, MAPE presents a relative assessment by quantifying the mean percentage deviation between forecasted and actual outcomes, illuminating the comparative accuracy of predictions. These metrics together contribute to a discerning understanding of the predictive capabilities of the models, spotlighting their precision and elucidating errors in terms of both their magnitude and proportionality [22]. A graphical representation of MAE values can be viewed in Figure 4, aiding in a visual evaluation of model efficacy and predictive analysis.

Residuals were subsequently computed using the formula:

$$RE = R_v - P_v \quad (8)$$

where, R_v denotes the actual value, P_v signifies the forecasted value, and RE stands for the computed residuals. Following this initial phase, the modeling process transitioned to its second stage, in which the BGP-FNN method was employed for modeling the sequence of residuals. The objective function of BGP is perceived as a stochastic function with a Gaussian process distribution in an optimization based on the Gaussian process. A Gaussian process represents a collection of random variables, any finite number of which exhibit joint normal distribution. It is characterized by a mean function $m[x]$ and a covariance function $k[x, x']$, delineating the similarity between two distinct points. This Gaussian process is engaged in optimization to depict the distribution of objective function values across varying locales in the hyperparameter space.

A neural network architecture consisting of two hidden layers and a fully connected output layer was utilized. In the implementation of the BGP-FNN model, neurons in the first hidden layer ranged between 8 and 64, whereas the second hidden layer comprised between 2 and 16 neurons. The precise neuron count for the final model was determined by the BGP, which searched for the optimal combination of hyperparameters to enhance performance on the training data. Within the hidden layers of the neural network, a 'tanh' activation function, representing the hyperbolic tangent function, was adopted. Specifically, the first hidden layer of the BGP-FNN was configured with 36 neurons, while the second layer contained 16 neurons. The training process for the BGP-FNN was orchestrated using the 'Adam' optimizer, denoting the Adaptive Moment Estimation method.

For a comprehensive evaluation, the combined PROPHET-BGP-FNN model was benchmarked against SARIMAX, PROPHET, and LSTM models, each applied to the tourist arrival dataset. Table 2 offers a detailed juxtaposition of the results derived from LSTM, SARIMAX, PROPHET models, and the SARIMA–CNN–LSTM model.

A comparative assessment of the various forecasting models yields profound insights into their predictive competencies. The PROPHET-BGP-FNN model consistently demonstrated superior outcomes in terms of MAE and MAPE. Remarkably, as depicted in Table 2 and Figure 4, the MAE and MAPE values associated with the PROPHET-BGP-FNN model surpassed those of the PROPHET, LSTM, and SARIMA models. The efficacy of the PROPHET-BGP-FNN model can be attributed to its amalgamation of techniques. The foundational component, PROPHET, adeptly captures inherent seasonality and trends present in the time series data. Concurrently, the BGP-FNN excels at discerning intricate, nonlinear patterns in the dataset. This integration, complemented by Bayesian optimization, offers automated and efficient hyperparameter tuning, optimizing the model's performance.

While LSTM models, celebrated for their DL capabilities in time series forecasting, occasionally grapple with capturing complex patterns and mitigating vanishing gradients, the SARIMAX model, robust in addressing seasonality, sometimes falters in decoding non-linear patterns. Conversely, the PROPHET model, efficient in discerning seasonality and trends, witnesses performance augmentation when combined with the non-linear capabilities of the BGP-FNN.

In essence, the PROPHET-BGP-FNN model emerges as a paramount solution for forecasting tourist arrivals, combining the strengths of multiple techniques while adeptly navigating the intricacies of tourism demand data. The synergetic fusion in the PROPHET-BGP-FNN model—where Prophet discerns trends, BGP identifies non-linear patterns, and FNN perceives temporal dependencies—equips it to supersede the limitations inherent to individual techniques. Thus, it furnishes predictions embodying both deterministic and stochastic attributes of time series data, marking the PROPHET-BGP-FNN model as an innovative and reliable approach in forecasting tourist influx.

The amalgamation of PROPHET, BGP, and FNN within a cohesive framework highlighted the potential of model integration to address intricate forecasting challenges. Forecasts from both the hybrid PROPHET-BGP-FNN model and the standalone PROPHET model were subjected to tests, with the predictive outputs presented in Figure 5. In Figure 5, the blue solid line depicts the actual tourist count, while the orange and green lines represent the predictions derived from the PROPHET and PROPHET-BGP-FNN models, respectively. The horizontal axis marks the indices of the test data, and the vertical axis signifies the count of tourists. A comparison between predicted and actual tourist counts revealed an intrinsic capability of the model to discern non-linear characteristics within the data, thereby confirming its enhanced predictive potential.

Table 2. Comparative performance of various models

Model	Error Parameter	
	MAE	*MAPE*
Total		
LSTM	1594.2794	0.1021
SARIMAX	1296.1470	0.0701
PROPHET	1017.5928	0.0534
PROPHET-BGP-FNN	800.1456	0.0408
Oahu		
LSTM	862.4400	0.0948
SARIMAX	518.0968	0.0556
PROPHET	500.4545	0.0511
PROPHET-BGP-FNN	436.2134	0.0385
Maui		
LSTM	555.8937	0.1176
SARIMAX	518.7983	0.1031
PROPHET	412.8093	0.0791
PROPHET-BGP-FNN	371.8901	0.0722
Big Island		
LSTM	234.4733	0.1063
SARIMAX	221.6927	0.0966
PROPHET	189.6114	0.0768
PROPHET-BGP-FNN	170.3490	0.0592
Kauai		
LSTM	271.5920	0.0742
SARIMAX	170.2401	0.0715
PROPHET	191.7744	0.0868
PROPHET-BGP-FNN	180.5601	0.0753
From Japan		
LSTM	291.5920	0.1759
SARIMAX	135.8123	0.0753
PROPHET	220.7038	0.0868
PROPHET-BGP-FNN	162.2541	0.0806
From other country		
LSTM	272.4966	0.0971
SARIMAX	182.6789	0.0681
PROPHET	196.5215	0.0719
PROPHET-BGP-FNN	107.3193	0.0307

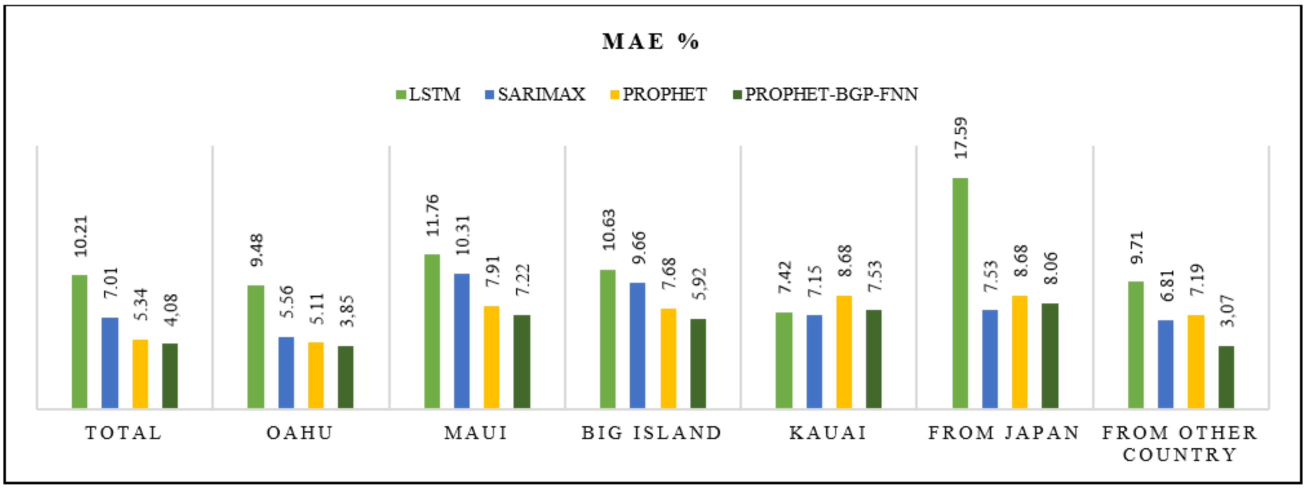

Figure 4. Comparative MAE of distinct models

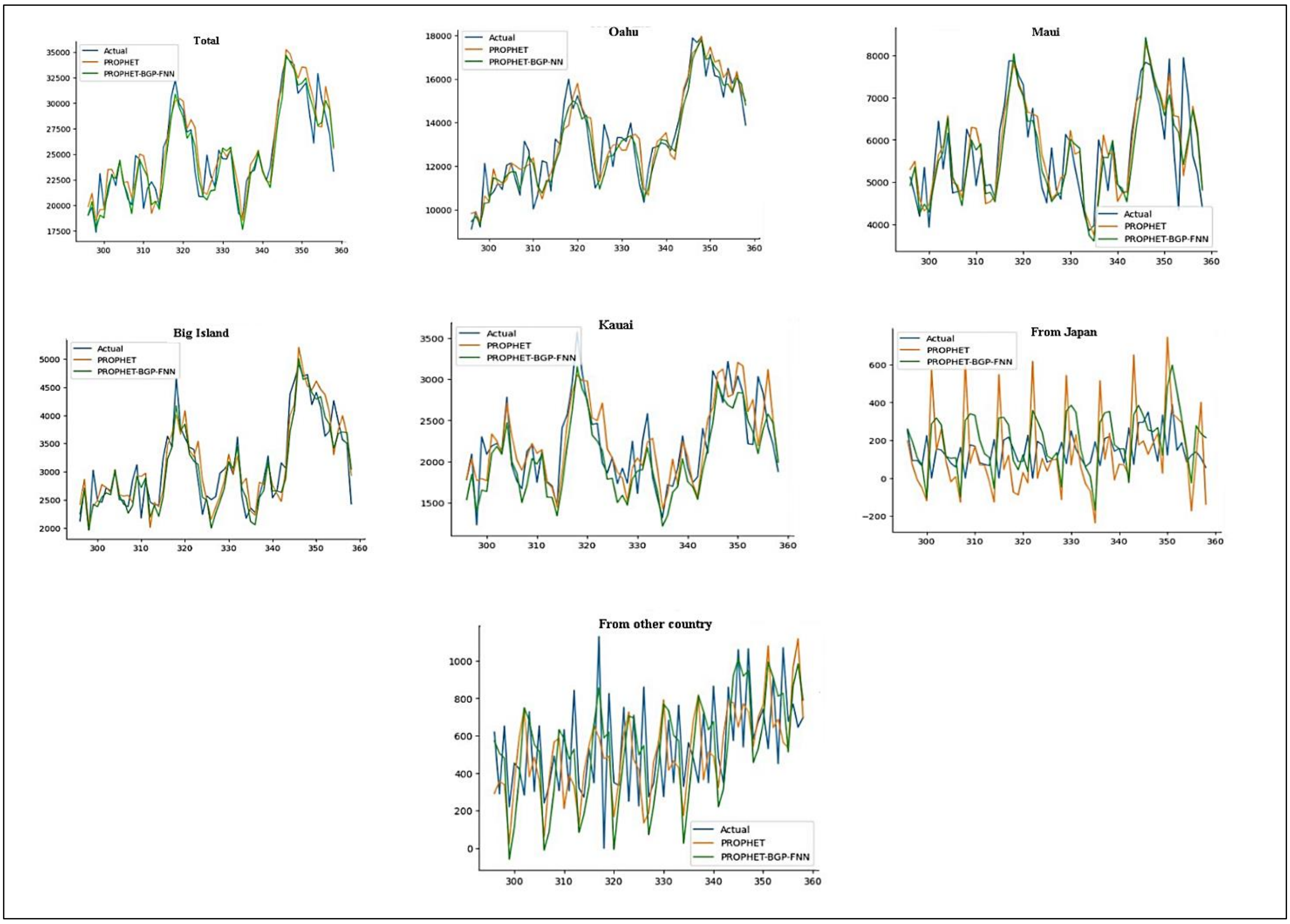

Figure 5. Contrast between the predicted trajectory of the PROPHET, PROPHET-BGP-FNN model, and the true value trajectory

In this study, an exhaustive suite of both traditional and advanced forecasting models was evaluated, culminating in the novel PROPHET-BGP-FNN model tailored for predicting tourist arrivals. The efficacy and limitations of each model were critically examined, with the PROPHET-BGP-FNN model emerging as the superior methodology. This superiority was further validated through its consistently lower MAE and MAPE values across diverse categories of tourist arrivals. Not only does the PROPHET-BGP-FNN model adeptly decipher deterministic and stochastic facets of time series data, but it also presents a pivotal solution for real-world applications.

For practical implications, the accurate forecasts provided by the PROPHET-BGP-FNN model have the potential to revolutionize decision-making processes within the tourism sector. Tourism agencies might leverage such precise predictions for a myriad of decisions ranging from resource allocation and staffing to formulating marketing strategies and infrastructure development. Furthermore, entities such as hotels, airlines, and other tourism-affiliated establishments could refine their operations predicated on projected tourist inflows, thus ensuring service excellence during high-demand seasons and circumventing excess capacity during off-peak times. By offering actionable insights, the PROPHET-BGP-FNN model stands poised to substantially elevate the operational efficiency and profitability within the tourism industry. In environments replete with challenges, high accuracy in predictions was achieved, underscoring the model's prospective utility in scenarios where precision in forecasting is of paramount importance for judicious decision-making.

4. CONCLUSIONS

In the presented research, DL algorithms, notably the PROPHET-BGP-FNN model, were implemented and evaluated for their efficacy in forecasting daily visitor arrivals in Hawaii. The study was delimited to data solely sourced from Hawaii, implying the potential for further exploration with extended time series datasets and diverse geographical locales. Remarkable success was achieved with the approach, displaying superior performance over traditional models like SARIMAX, PROPHET, and LSTM. Through the synergetic fusion of PROPHET, BGP, and FFNN models, a novel and proficient tool for univariate tourism demand forecasting was introduced. These findings underscore the latent potential of DL and hybrid models within the sphere of tourism forecasting—a domain relatively untapped hitherto.

The methodology delineated here innovatively employs PROPHET to distill the linear component of tourist arrivals, while the BGP-FNN model adeptly discerns intricate nonlinear patterns. Such a hybrid strategy not only exhibits formidable predictive accuracy but also demonstrates adaptability to the nuanced complexities intrinsic to tourist arrival datasets. While empirical analyses accentuated the PROPHET-BGP-FNN model's robust predictive capabilities, it is acknowledged that continuous and rigorous evaluations are paramount for future research endeavors.

Future prospects encompass refinement endeavors, encompassing hyperparameter fine-tuning and topological redesigns of the PROPHET-BGP-FNN model. Extending the model's scope, beyond the confines of Hawaiian data and venturing into longer time series datasets from varied locations, could further solidify the model's reliability and applicability.

While challenges and unexpected outcomes were encountered during the research, the evident superior performance of the PROPHET-BGP-FNN model over conventional counterparts heralds a potential paradigm shift in tourism forecasting. With meticulous refinement and broader exploration, this model might assume a seminal role in bolstering decision-making processes not only within the tourism sector but in diverse industries that rely on precise forecasting.

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