

¹Lei Wang²Xiaorong Jiang

Time Series Analysis and Neural Network Optimization of Tourist Destination Heat Prediction Model



Abstract: - Accurate prediction of tourist destination heat is significant for effectively managing tourist flow in the tourism industry. However, forecasting the temperature of a tourist destination is challenging, and various factors, like weather conditions, influence it. In this study, we proposed a novel hybrid strategy using time series analysis and neural network optimization to predict tourist destination heat accurately. The study commences with collecting historical tourist visitation data, weather records, and other information. Then, the raw database was preprocessed to make the data effective and reliable for subsequent analysis. Further, the Autoregressive Integrated Moving Average (ARIMA) technique was employed as a time series analysis technique, capturing and identifying the database's underlying patterns and correlations. Consequently, a Fire Hawk Optimizer-based Dense Recurrent Neural Network (FHO-DRNN) was developed and trained using the ARIMA outcomes to predict the tourist destination heat. The proposed framework was implemented in the MATLAB software, and the results are examined in terms of accuracy, Mean Absolute Error (MAE), and computational time. Furthermore, we compared the existing predictive models to validate the proposed model's effectiveness in forecasting tourist destination heat.

Keywords: Tourism Management, Dense Recurrent Neural Network, Autoregressive Integrated Moving Average, Fire Hawk Optimizer

1. INTRODUCTION

Tourism is one of the driving factors of a country's economic growth and cultural landscape. Effective management of tourism enables the maintenance of sustainable economic growth and the preservation of cultural heritage. In recent decades, climate change, such as rising temperatures, adversely impacted the tourism industry [1]. The rise of temperature or heat makes the tourist uncomfortable and may lead to several health complications such as dehydration, sunburn, etc. Also, it may impact their traveling experiences and degrade the sustainability of the tourist destination. Hence, an accurate forecasting of heat is significant for reliable and effective tourism management. By analyzing the weather data and climatic conditions using advanced analytics tools, the heat prediction intends to assist tourism management in implementing timely measures to safeguard tourists from rising temperatures. In addition, it optimizes the tourism infrastructure and provides sustainable tourism [2].

Initially, the studies forecasted heat by analyzing the historical data using time series analysis. The time series assessment involves investigating previous temperature data to identify trends and patterns. However, the intermittent nature of weather and climatic conditions poses significant challenges to these statistical methods [3]. Hence, an advanced analytics algorithm is needed to accurately predict heat in tourist destinations. The evolution of artificial intelligence techniques, such as machine learning, deep learning, reinforcement learning, etc., paved the way for the development of accurate heat prediction models. These techniques can examine large volumes of data and automatically identify patterns through intensive learning [4].

In recent years, many predictive models have been designed using advanced techniques such as Support Vector Machine (SVM), K-nearest Neighbor (KNN), neural networks, etc., to accurately predict heat. Although these models obtained better accuracy and performance than the conventional statistical models, they need large

¹ School of Tourism and Economic Management of Nanchang Normal University, Nanchang, Jiangxi, 330032, China

² School of Marxism, Nanchang Normal University, Nanchang, Jiangxi, 330032, China

*Corresponding author e-mail: 15270018040@163.com

Password 219940Aa

mail.163.com

Xiaorong Jiang: r314552533@163.com

Copyright © JES 2024 on-line : journal.esrgroups.org

computational resources and data for training the system [5]. Moreover, these techniques often require fine-tuning mechanisms and offer limited scalability, reliability, and adaptability to real-time scenarios. To resolve these issues, we proposed a collaborative framework, which uses the time series analysis and optimized neural network to accurately predict heat in tourism destinations.

The article is organized as follows: section 2 presents the literature survey, section 3 provides the system model and problem statement, section 4 depicts the proposed strategy, section 5 examines the proposed strategy's outcomes, and section 6 provides the article conclusion.

2. RELATED WORKS

A few recent studies associated with tourist destination heat prediction are reviewed below,

Evripides Christodoulou et al. [1] presented an evaluation algorithm to examine the influence of weather on tourist revisit intention. This study utilized classification and natural language processing to evaluate weather factors. This study was conducted based on the online reviews gathered during the summer months between 2010 and 2019 from persons who visited Cyprus. Further, it utilized an ensemble gradient-boosting mechanism for predicting the intention to revisit the tourist, and a Shapley additive explanation-based interpretation technique was used to interpret the classifier patterns. However, this study failed to address the adverse influence of climatic conditions on sustainable tourism. Diego R.-Toubes et al. [2] proposed a study to analyze the impact of weather conditions on the tourist's behavior in a beach destination. This study examined the interconnection of weather criteria with daily flows during the high season in beach destinations in north-west Spain. The study results showed that the hours of sunshine have a greater influence on tourist behavior, which is the most influential factor. However, the study has not considered different weather seasons, which limits its applicability and reliability.

Lindsay Matthews et al. [3] developed a data-driven weather index prediction mechanism for beach park tourism. This prediction framework uses mathematical optimization, expert knowledge, and visitor preferences to create a climate index. This index allocates daily weather scores per four parameters: comfort, cloud cover, wind speed, and precipitation. The implementation results suggest that this optimized index strongly fits the observed visitation and assists in quick decision-making of destination managers and tourism marketers. This study failed to examine the dynamic nature of tourism. Wenxing Lu et al. [4] developed a deep-learning model to predict the tourist flow using the Improved Gated Recurrent Unit (GRU). This algorithm introduced an enhanced attention module to the encoding-decoding module, which is integrated with the GRU. This study used the tourist flow database collected from the popular Huangshan Scenic Area in China, and the implementation results depict that the web search index and climate comfort index prediction assist in reliable and effective tourism management. However, this methodology is less scalable and adaptive to changing climatic conditions. Ying Wang et al. [5] developed a study to analyze the impact of air quality and weather conditions on tourism. This study utilized geo-tagged check-in user-generated content to capture the sentiments underlying the on-site emotional experience of the tourists. This study proves that the air quality and other weather conditions influence the psychological and emotional characteristics of the tourist. However, this study is limited to data, and it is time-consuming.

3. SYSTEM MODEL AND PROBLEM STATEMENT

In recent years, tourism has witnessed exponential growth as millions travel to different places to explore cultural and adventure experiences. However, the tourism industry is greatly influenced by weather conditions, particularly the extreme heat conditions that significantly influence the traveler's comfort, and may lead to several health complications such as dehydration, sunburn, etc. Therefore, predicting the heat in tourist destinations is essential for the optimal management of the tourism industry. A typical system model of tourism destination heat prediction model includes data acquisition, data preprocessing, and prediction model. The data acquisition module collects historical weather data of each tourism destination, filtered using the data preprocessing module. This module cleans the gathered data by handling missing values, outliers, and inconsistencies, which ensures uniformity and consistency in the database. The prediction module includes machine learning (ML) architectures, deep learning (DL), or transformers to forecast the heat. These algorithms

learn the trends and patterns of heat in tourist places through intensive training using the preprocessed dataset. Although these predictive models automatically forecast the heat in tourist destinations, certain challenges are described below.

- ❖ The deep learning architectures require high-quality weather data for training, which makes them ineffective under resource-constrained conditions.
- ❖ Analyzing large-scale weather databases using the DL architectures demands substantial computational resources, which makes the system costly and resource-intensive.
- ❖ Deep learning models involve certain hyperparameters, such as weights, bias, etc. Tuning these parameters to their optimal range is required to ensure the models' effective training.
- ❖ DL and ML models must generalize well to unseen data to make accurate predictions in real-world scenarios. However, overfitting to training data makes it ineffective to capture the underlying patterns in the data, leading to poor generalization.
- ❖ Conversely, conventional models have difficulty ensuring scalability and reliability in real-time scenarios, where the volume of weather data varies.

To resolve these issues, we proposed a collaborative framework combining the efficiency of time-series analysis, deep learning, and meta-heuristic optimization algorithms for precise and reliable prediction of heat in tourist destinations.

4. PROPOSED METHODOLOGY FOR TOURIST DESTINATION HEAT PREDICTION

A novel hybrid predictive model was developed in this article by incorporating time series analysis and an optimized neural network for accurate and reliable prediction of heat in tourist destinations. The primary concern of the developed work is to address the challenges associated with traditional heat prediction methods and improve the accuracy and reliability of heat forecasts in tourist destinations. Combining the strengths of time series analysis and optimized neural networks, the developed model aims to provide more accurate predictions that account for the complex temporal patterns and dynamics inherent in heat data. Figure 1 presents the architecture of the developed framework.

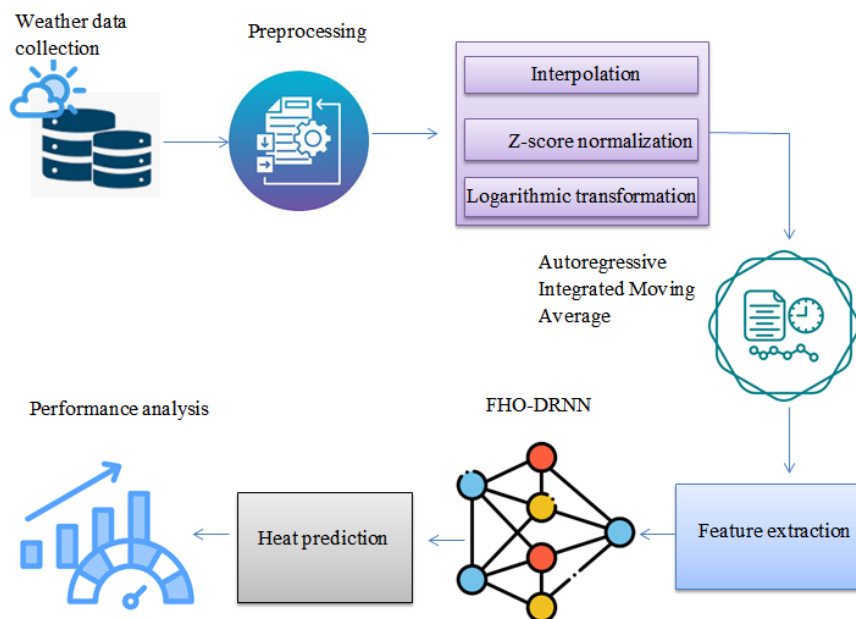


Figure 1: Architecture of the proposed strategy

The proposed methodology commences with collecting weather data from different tourist destinations. Secondly, the collected database was preprocessed to improve its quality. Then, the autoregressive integrated moving average was employed to analyze the trends and important features in the database. Finally, a hybrid FHO-DRNN was developed to forecast the heat in tourist destinations. The DRNN component in the developed model was trained using the outcomes of the time series module. At the same time, the FHO continually refines the DRNN hyperparameters to their optimal range to improve its training process.

4.1 Data Collection and Preprocessing

The first phase in the predictive framework is the data collection, where comprehensive weather data is collected from multiple tourist destinations. Since the heat levels of the place are highly influenced by weather conditions like solar irradiance level, wind speed, humidity, etc., we intend to accumulate and gather a database containing weather data. The proposed study utilized the publicly accessible weather database from the net source. This database contains meteorological variables like temperature, wind speed, precipitation, humidity, etc., and it is fed into the system for training and heat prediction.

After the data collection phase, the collected database undergoes preprocessing steps to improve its quality, which assists in improving the speed and accuracy of subsequent analysis. The data preprocessing steps include missing value handling, outlier detection, and normalization. Missing value handling indicates the process of handling databases with missing data points. In this step, the missing values in the database are replaced with data points estimated based on the known data points. In the developed work, we utilized polynomial interpolation to handle missing values. This method determines missing values by fitting a polynomial function to a sequence of data points. The second step in data preprocessing is outlier detection. Outlier detection defines the process of detecting database data points that deviate from other data points. In the proposed work, we utilized the z-score algorithm to detect these outliers. Finally, data normalization was performed using log transformation. The logarithmic transformation technique applies natural logarithm to the data points to address skewness in the database. This step enables the transformation of the data into a more symmetrical distribution. These steps convert the raw database into an appropriate format, which will make subsequent analysis easier.

4.2 Autoregressive Integrated Moving Average

An ARIMA is a time series analysis algorithm that combines the strength of one dependent variable relative to other changing variables. This algorithm is widely deployed for forecasting the future outcomes by analyzing the historical time-series data [6]. In the proposed work, it was utilized to examine the trends and underlying patterns in the preprocessed weather data. The ARIMA model contains three components, namely, autoregression (AR), integrated (I), and moving average (MA). The AR component captures the relationship between a variable and its past values. The I component indicates the differencing of raw observations, which makes the time series stationary. Finally, the MA component integrates the observation and residual error dependency. The mathematical equations for the above components are expressed in Eqn. (1), (2), and (3).

$$D_t = G + \lambda_1 D_{t-1} + \lambda_2 D_{t-2} + \dots \dots \dots \lambda_n D_{t-n} + \alpha_t \quad (1)$$

$$\Delta D_t = D_t - D_{t-1} \quad (2)$$

$$D_t = \kappa + \alpha_t + \mu_1 \alpha_{t-1} + \mu_2 \alpha_{t-2} + \dots \dots \dots + \mu_m \alpha_{t-m} \quad (3)$$

Where D_t denotes the value of the time series at time t , G indicates the constant term, λ defines the parameters that need to be determined, α_t denotes the error term, and κ defines the series mean. These components enable us to analyze and identify the most significant features that highly influence heat patterns. The outcomes of ARIMA were fed as input to the DRNN block for heat prediction.

4.3 Dense Recurrent Neural Network

A DRNN is a type of artificial neural network that is highly deployed for examining patterns in time-series data. The neural architecture of DRNN incorporates an additional dense layer between the recurrent layers of conventional RNN to capture complex, intricate patterns and temporal dependencies within the data [7]. In addition, utilizing dense layers helps resolve the vanishing gradient problem in the traditional RNN system. In the proposed work, we utilized RNN to predict the heat in tourist destinations by analyzing patterns in historical weather data. The DRNN architecture includes four layers: input, recurrent, dense, and output. The input layer accepts the output of the time-series analysis as input. The recurrent layer processes the input data sequence over time. Here, we utilized Long Short-Term Memory (LSTM) to capture the input sequence's complex intricate patterns and long-range dependencies. The LSTM cell includes the input gate, forget gate, output gate, candidate cell state, cell state, and hidden state for processing the input sequence and capturing the patterns to forecast the heat, and they are mathematically represented in Eqn. (3), (4), (5), (6), and (7).

$$I_t = \sigma(w_i \cdot [h_{t-1}, x_t] + b_i) \quad (3)$$

$$F_t = \sigma(w_f \cdot [h_{t-1}, x_t] + b_f) \quad (4)$$

$$O_t = \sigma(w_o \cdot [h_{t-1}, x_t] + b_{og}) \quad (5)$$

$$\hat{C}_t = \tanh(w_c \cdot [h_{t-1}, x_t] + b_c) \quad (6)$$

$$h_t = O_t * \tanh(\hat{C}_t) \quad (7)$$

Where σ represents the sigmoid activation function, \tanh denotes the hyperbolic tangent activation function, w_i, w_f, w_o, w_c and indicates the weight matrices of input gate, forget gate, output gate, and cell state, b_i, b_f, b_{og} , and b_c refers to the bias vectors of input gate, forget gate, output gate, and cell state, h_t defines the hidden state, \hat{C}_t denotes the cell state, I_t represents the input gate, and F_t defines the forget gate. These gates and states capture long-range dependencies and patterns within the input sequence. The input gate selectively estimates what information or feature should be retained from the current input sequence, while the forget gate regulates the flow of information (it controls what information or feature should be discarded). Consequently, the output gate controls the information flow to the next hidden state, while the candidate cell state integrates new information into the cell state, enabling it to adapt to the changing trends and patterns in the weather data. The hidden state is the output of the LSTM unit, which captures the most significant patterns and trends in the data. The output of the LSTM unit is fed into the dense layer. The dense layers are fully connected layers in which each neuron is interconnected to every neuron in the recurrent layer and output layer. This layer estimates the complex patterns and relations in the data, which enables it to predict the heat. The output of the dense layer is represented in Eqn. (8).

$$Ds_t = \sigma(W_d \cdot h_t + b_d) \quad (8)$$

Where W_d and b_d defines the weight matrix and bias vector of a dense layer. The output of the dense layer is forwarded into the output layer of DRNN architecture, which forecasts the heat based on the learned patterns and trends. The output of the DRNN is mathematically represented in Eqn. (9).

$$Hp_t = (W_o \cdot Ds_t + b_o) \quad (9)$$

Where W_o and b_o indicate the weight matrix and bias vector of an output layer. This layer provides the heat value or level based on historical observations. Although the DRNN effectively analyzes sequential data, its performance is highly influenced by the training process. In the training phase, the model parameters, including weight, bias, number of neurons, etc., are adjusted iteratively to enhance prediction accuracy. In the proposed model, we utilized FHO for refining the model parameters to their optimal range.

4.4 Optimization

We utilized FHO to refine the DRNN model parameters in the proposed work. The FHO is a meta-heuristic optimization algorithm that imitates fire hawks' foraging characteristics, including setting and spreading fires and catching prey. The objective function of FHO changes based on the problem statement. Here, the objective function is to minimize the MAE by fine-tuning the values of the model parameters to its optimal value. The optimization process begins with the random initialization of the candidate solutions. The candidate solution indicates the value of model parameters, and the population size defines the number of candidate solutions. Then, the fitness value of each candidate solution was determined based on the pre-defined objective solution. The fitness value defines the DRNN's performance for the corresponding parameter values. If the fitness value is high, the error incurred by DRNN is minimum and vice versa. Further, new candidate solutions are determined by updating and fine-tuning the current candidate solutions. The updating of candidate solutions is represented in Eqn. (10).

$$Mp'_i = Mp_i + (r_1 \times B_{mp} - r_2 \times Mp_{rn}), i = 1, 2, 3, \dots, k \quad (10)$$

Where Mp'_i indicates the new candidate solutions, r_1 and r_2 denotes random numbers, k refers to population size, B_{mp} defines the candidate solution with high fitness, and Mp_i current value of the model parameters. After the updation process, the fitness values are determined for new candidate solutions. Finally, the parameter set with higher fitness value was selected as DRNN model parameters. This parameter optimization is an interactive mechanism and it continuously refines the model parameters, leading to enhanced prediction accuracy and optimal training.

5. RESULTS AND DISCUSSION

In this study, we developed an innovative approach for predicting heat in tourist destinations using the combination of time-series analysis and neural network optimization. The developed algorithm utilizes the historical weather data collected from multiple tourist destinations. The presented methodology employs Autoregressive Integrated Moving Average for analyzing the trends and patterns in the data. This time series analysis enables us to capture and extract the trends, which is utilized by the neural network for forecasting heat. Finally, the FHO-DRNN was trained using the extracted trends and patterns to predict the heat level. The proposed strategy was modeled in the MATLAB tool, version R2020a, running on 64-bit Windows 10 Operating System. The results of the study are examined in terms of accuracy, MAE, RMSE, and computational time.

5.1 Performance analysis:

In this section, we analyzed the performances of the proposed algorithm through intensive training and testing. Firstly, the input database was split into ratios of 80:20 for the training and testing process. Here, the performances are assessed in terms of accuracy and loss by increasing the iteration count from 0 to 2400. The learning rate of the FHO-DRNN was fixed at 0.04, and epoch count is 50. The training accuracy measures how effectively the developed algorithm learns the trends and patterns of heat in tourist destinations. Consequently, the validation accuracy quantifies how effectively the developed model applies the learned patterns and trends and forecasts the heat on the unknown data samples. The intensive evaluation of accuracy performances in training and validation phase depicts that it achieved approximately 95.5%, and 90% accuracy. This highlights that the developed algorithm precisely learns the trends and predicts the heat in tourist destinations. Figure 2 depicts the model's training and validation performances.

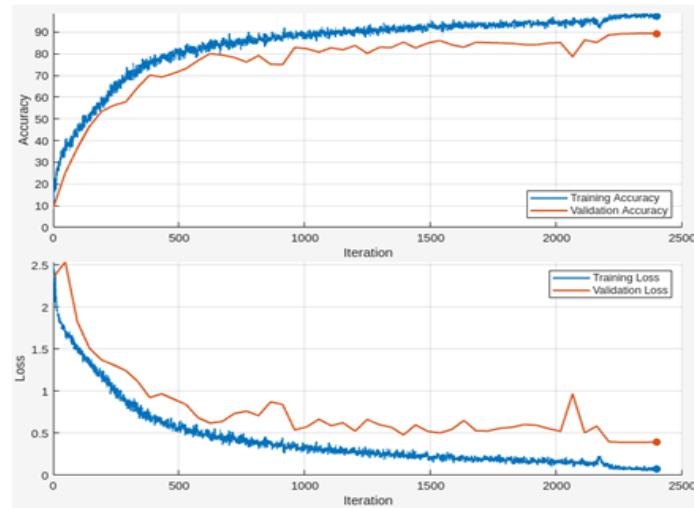


Figure 2: Training and validation performances

Similarly, we determined loss performance of the proposed FHO-DRNN to evaluate false predictions made by the system. The training loss measures the difference between the actual and predicted heat levels in the training sequence. It enables us to assess how effectively the proposed strategy fits into the training set. On the other hand, the validation loss quantifies the deviation between the actual and the predicted heat levels on the unseen data (data other than training sequence). This enables us to evaluate how the proposed strategy prevents overfitting and provides generalization.

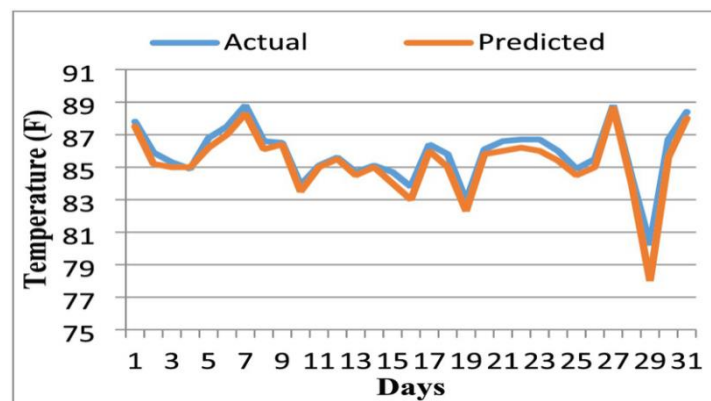


Figure 3: Predicted and actual heat distribution

From the analysis, it is observed that the developed algorithm obtained minimum training and validation losses of 0.1 and 0.4, respectively. This minimum loss performance manifests that the designed predictive model accurately forecasts the heat in tourist destinations. The predicted and actual heat distribution is graphically presented in Figure 3. The x-axis indicates the days, while the y-axis indicates the temperature (heat) in Fahrenheit (F). The actual value represents the real temperature values obtained from historical records. These values serve as the reference for evaluating the performance of a predictive model. On the other hand, the predicted values represent the heat forecasted by the proposed FHO-DRNN model, and it is obtained by examining the patterns, trends and other relevant features in the historical weather data. From the graphical analysis, it is evident that the predicted values match with the real observations, highlighting the model's accuracy in heat prediction.

5.3 Comparative assessment

In this module, we compare the performances of the proposed model with the conventional techniques to validate its effectiveness and robustness in heat prediction. The existing techniques utilized for comparative assessment include Support Vector Machine (SVM) [8], K-Nearest Neighbor (KNN) [9], Long Short Term

Memory (LSTM) [10], Deep Feed forward Neural Networks (DFNN) [11], and Temporal Convolutional Neural Network (TCNN) [12]. The parameters utilized for comparative analysis include accuracy, MAE, and computational time.

Accuracy metric measures how precisely the developed model predicts the heat in tourist destinations. It quantifies the overall correctness of the proposed model in forecasting heat levels. Here, we determined the accuracy of both proposed and existing models for increasing data volumes to manifest the scalability and reliability of the techniques. The existing techniques such as SVM, KNN, DFNN, LSTM, and TCNN obtained an average accuracy of 90.02%, 80.39%, 89.18%, 94.01%, and 92.13%, respectively, while the proposed predictive model achieved an average accuracy of 99.49%. The improved accuracy rate manifests that the developed model predicts the heat in tourist destinations more precisely than the conventional algorithm. In addition to this, it is noticed that the designed algorithm almost maintains consistent accuracy over increasing data volume, highlighting its scalability and reliability over real-time scenarios. Figure 4 (a) depicts the comparative analysis of accuracy.

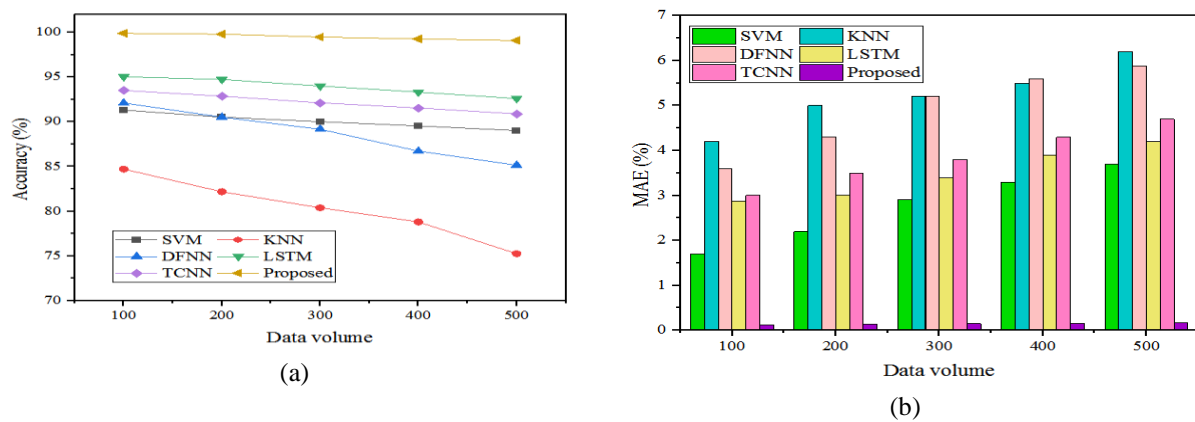


Figure 4: Performance evaluation with existing models: (a) accuracy, (b) MAE

Consequently, the MAE achieved by the proposed strategy was evaluated with the conventional models, and it is graphically presented in Figure 4 (b). The MAE measures the performance of the heat prediction models by quantifying the average absolute difference between the predicted and actual values.

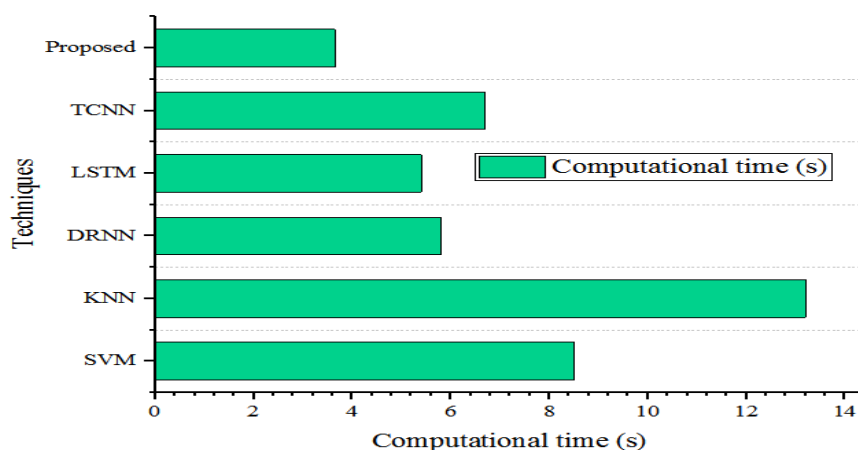


Figure 5: Computational time analysis

The conventional models, such as SVM, KNN, DFNN, LSTM, and TCNN, attained an average error rate of 2.90%, 5.20%, 5.20%, 3.40%, and 3.80%, respectively. However, the proposed FHO-DRNN model earned a minimum error rate of 0.147%. This highlights that the developed predictive model predicts the heat more accurately than the existing models. Finally, the computational efficiency of the proposed model was compared

with the conventional algorithms. The computational time indicates the time the predictive model consumes for performing tasks like data preprocessing, prediction, optimization, model training, etc. The existing techniques, such as SVM, KNN, DFNN, LSTM, and TCNN, consumed 8.5s, 13.2s, 5.8s, 5.4s, and 6.7s, respectively, while the developed algorithm consumed a minimum time of 3.65s, which is tabulated in Table 1 and Figure 5.

Table 1: Computational time assessment

| Steps | Time (s) |
|----------------------|----------|
| Data Preprocessing | 0.50 |
| Time Series Analysis | 0.80 |
| Prediction | 0.60 |
| Training | 1.00 |
| Optimization | 0.75 |
| Total | 3.65 |

The comparative assessment proves that the proposed strategy earned greater accuracy, minimum MAE, and computational time than conventional models. This validates its precision and efficiency in predicting heat in tourist destinations.

6. CONCLUSION

This study proposed an innovative predictive model for forecasting the heat in tourist destinations using a combination of time-series analysis and an optimized neural network. The developed work utilizes ARIMA-based time series analysis algorithm for capturing the underlying patterns and trends in the historical data, which is utilized to train the optimized neural network for predicting heat. The optimized neural network integrates FHO with the DRNN for optimal and accurate heat prediction. The proposed model is executed in the MATLAB tool, and the results are examined as accuracy, MAE, and computational time. The simulation results depict that the developed FHO-DRNN model achieved higher accuracy of 99.49%, minimum error rate of 0.149%, and reduced computational time of 3.65s. In addition, a comparative assessment was conducted with the existing prediction algorithms including SVM, KNN, DFNN, LSTM and TCNN to highlight the proposed model's efficiency and robustness in heat prediction. The comparative analysis demonstrates that in the proposed model the parameters such as MAE and computational time are reduced by 2.05% and 1.74s, while the accuracy metric was improved by 5.48%. Also, the developed predictive algorithm maintained a consistent performance irrespective of increasing data volumes, which highlights its scalability and reliability in real-time heat prediction.

Acknowledgement

Jiangxi University Humanities and Social Sciences Research Youth Program "Research on the Strategy of Creating the Best Destination for Study Tour in Jiangxi Province" (No. GL22236)

REFERENCES

1. Christodoulou, Evripides, et al. "Evaluating the Effect of Weather on Tourist Revisit Intention using Natural Language Processing and Classification Techniques." 2021 IEEE International Conference on Systems, Man, and Cybernetics (SMC). IEEE, 2021.
2. R.-Toubes, D., Araújo-Vila, N., & Fraiz-Brea, J. A. (2020). Influence of Weather on the Behaviour of Tourists in a Beach Destination. *Atmosphere*, 11(1), 121.
3. Matthews, L., Scott, D., & Andrey, J. (2021). Development of a data-driven weather index for beach parks tourism. *International journal of biometeorology*, 65, 749-762.
4. Lu, Wenxing, et al. "Intelligence in tourist destinations management: Improved attention-based gated recurrent unit model for accurate tourist flow forecasting." *Sustainability* 12.4 (2020): 1390.

5. Wang, Ying, et al. "Effects of air quality and weather conditions on Chinese tourists' emotional experience." *Journal of Hospitality and Tourism Management* 48 (2021): 1-9.
6. Schaffer, Andrea L., Timothy A. Dobbins, and Sallie-Anne Pearson. "Interrupted time series analysis using autoregressive integrated moving average (ARIMA) models: a guide for evaluating large-scale health interventions." *BMC medical research methodology* 21 (2021): 1-12.
7. Han, Jung Min, et al. "Using recurrent neural networks for localized weather prediction with combined use of public airport data and on-site measurements." *Building and Environment* 192 (2021): 107601.
8. Deif, Mohanad A., et al. "A hybrid multi-objective optimizer-based SVM model for enhancing numerical weather prediction: A study for the Seoul metropolitan area." *Sustainability* 14.1 (2021): 296.
9. Kareem, Fairoz Q., Adnan Mohsin Abdulazeez, and Dathar A. Hasan. "Predicting weather forecasting state based on data mining classification algorithms." *Asian Journal of Research in Computer Science* 9.3 (2021): 13-24.
10. Liu, Y., Li, D., Wan, S., Wang, F., Dou, W., Xu, X., ... & Qi, L. (2022). A long short-term memory-based model for greenhouse climate prediction. *International Journal of Intelligent Systems*, 37(1), 135-151.
11. Hewage, Pradeep, et al. "Deep learning-based effective fine-grained weather forecasting model." *Pattern Analysis and Applications* 24.1 (2021): 343-366.
12. Hewage, Pradeep, et al. "Temporal convolutional neural (TCN) network for an effective weather forecasting using time-series data from the local weather station." *Soft Computing* 24 (2020): 16453-16482.