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RESEARCH ARTICLE

The Convolutional Neural Network Text Classification Algorithm in the Information Management of Smart Tourism Based on Internet of Things

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ABSTRACT The relentless progression of advanced technologies has driven the seamless integration of Internet of Things (IoT) services into the fundamental framework of contemporary tourism enterprises. In the quest for valuable insights from the vast reservoir of tourism data, this study employs a Convolutional Neural Network (CNN) as its primary instrument, culminating in the development of a Convolutional Neural Network-Bidirectional Long Short-Term Memory (CNN-BiLSTM) model designed for the classification of textual data in the smart tourism domain. The primary function of this model is to conduct sentiment analysis on smart tourism data, specifically by categorizing review data into either positive or negative sentiments. The incorporation of review ratings further aids in the accurate labeling of data according to their respective sentiment categories, thus streamlining the process of effective data annotation. The empirical findings reveal distinctive performance trajectories for the three models concerning positive comments across various evaluation metrics. Remarkably, in terms of precision, the CNN-BiLSTM model leads with an impressive 87.9%, closely followed by the BiLSTM model at 87.4%, while the Text Convolutional Neural Network (TextCNN) model trails slightly at 85.3%. Similarly, the recall highlights the CNN-BiLSTM model's excellence, achieving an impressive 88.34%, compared to 78.5% for BiLSTM and 77.6% for TextCNN models. In the realm of accuracy, the CNN-BiLSTM model maintains its dominance at 85.1%, while the BiLSTM and TextCNN models achieve 82.7% and 81.4%, respectively. Notably, the CNN-BiLSTM model outperforms the trio in terms of the F1 value, securing a robust 85.41%. In summary, the CNN-BiLSTM model consistently demonstrates excellent performance across a range of metrics, including precision, recall, accuracy, and F1 value, signifying its supremacy in this classification task. This study presents a systematic solution for enhancing smart tourism services, thereby providing a strong foundation for the growth and advancement of tourism enterprises.

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INDEX TERMS Convolutional neural network, text classification algorithm, information management, smart tourism, accuracy, F1 value.

I. INTRODUCTION

A. RESEARCH BACKGROUND

The widespread integration of Internet of Things (IoT) technology in the tourism sector has continuously improved the informatization of tourism services, providing tourists with increased convenience [1], [2]. However, in parallel with the rapid growth of information, there has been an exponential increase in the volume of smart tourism data. Consequently, the efficient extraction of valuable insights from this data reservoir has become an imperative that needs to be tackled.

In this context, introducing the Convolutional Neural Network (CNN) text classification algorithm is important. Recognized as a powerful deep learning model, CNN has demonstrated impressive capabilities in various domains, including computer vision and natural language processing. By incorporating this model into the sphere of information management within smart tourism IoT services, it enhances the ability to analyze extensive text data and allows for a profound exploration of tourist emotions, preferences, and related insights [3], [4]. As a result, the driving force behind this study is to assess the suitability of the convolutional neural network text classification algorithm in addressing information management challenges within the realm of smart tourism IoT services. Additionally, the study aims to improve the quality and effectiveness of smart tourism services through this innovative approach.

B. RESEARCH OBJECTIVES

The main objective of this study is to investigate the integration of a CNN text classification algorithm as a means to provide robust support for information management within smart tourism IoT services. The specific goals of the study involve conducting a comprehensive analysis of the extensive textual data generated within the framework of smart tourism IoT services, aiming to understand its intrinsic value and associated challenges. This entails an examination of the applicability of convolutional neural networks in text classification and a thorough exploration of their potential advantages in the field of smart tourism. The study also involves developing and implementing a customized convolutional neural network text classification algorithm tailored to the specific needs of smart tourism IoT services. The primary purpose is to enable precise categorization and sentiment analysis of textual inputs, including tourists' reviews and feedback. Through empirical experiments and case study analyses, the study seeks to substantiate the effectiveness and feasibility of the proposed algorithm in real-world smart tourism scenarios, thereby establishing a scientifically supported foundation for information management initiatives.

C. RESEARCH FOUNDATION AND MOTIVATION

As smart tourism applications proliferate, a corresponding surge in textual data has emerged, encompassing visitor comments, ratings, and feedback. This accumulation of textual information has become a prominent trend within the tourism industry. The effective management and analysis of this extensive textual data are paramount for tourism enterprises and decision-makers. This significance arises from its potential to provide substantial support for enhancing service quality, meeting customer demands, and curating more enticing travel experiences. Incorporating sentiment analysis is a pivotal tool, enabling a deeper understanding of customer emotional experiences. It facilitates the comprehension of customer satisfaction levels, areas of interest, and potential pain points. Through sentiment analysis, there is an avenue to more precisely address customer needs, implement real-time adjustments informed by their feedback, and provide travel services that are both personalized and gratifying.

Deep learning technologies, particularly CNNs and Bidirectional Long Short-Term Memory networks (BiLSTMs), have achieved significant success in the fields of text classification and sentiment analysis. These technologies excel not only in managing extensive textual data but also in the automatic recognition of emotions, sentiment polarity, and relevant themes and features within the text. Incorporating these powerful deep learning tools into the context of smart tourism equips tourism enterprises with robust means to gain a more comprehensive understanding of customer emotions and requirements, ultimately enabling enhanced services [5].

This study is motivated by the necessity for comprehensively exploring the functionality of the CNN-BiLSTM text classification model. The model serves as a powerful instrument for executing sentiment analysis and managing textual data within the smart tourism domain. We systematically evaluate the model's performance in sentiment analysis and text processing to affirm its effectiveness in uncovering insights into customer sentiments and satisfaction. The overarching objective is to present innovative and actionable solutions for information management within the domain of smart tourism services, thereby laying a robust foundation for continuous development and innovation within the tourism industry. The fusion of deep learning technologies and sentiment analysis is postulated to unlock new opportunities and bestow competitive advantages upon the tourism sector, ultimately enhancing the overall travel experience.

II. LITERATURE REVIEW

Numerous scholars have dedicated their efforts to advancing this field. Deng et al. introduced an innovative text classification model that utilizes word2vec for training word vector representations. This model incorporates an attention mechanism for context vector computation to extract keyword information. Additionally, BiLSTM networks capture contextual features, while CNNs identify prominent topic features [6]. Puh and Babac employed a machine learning framework to extract sentiment and ratings from travel reviews. Their models were trained to classify reviews into positive, negative, or neutral sentiments, covering a rating scale from one to five. The results underscore the high predictive accuracy of machine learning models in discerning sentiments and ratings within tourist feedback [7]. Aljohani et al. proposed a deep learning-based context classification architecture. Unlike conventional feature-oriented citation classification models, this study incorporates focal loss and class weight functions within the CNN model to address class imbalance issues in citation classification datasets. The outcomes reveal improvements over baseline results. In tasks involving two-category and multi-category citation classification, the model achieved F1 values of 90.6 and 72.3, accompanied by accuracy rates of 90.7% and 72.1%, respectively [8].

The aforementioned research leveraged artificial intelligence technologies, including word2vec, BiLSTM networks, and CNN, for sentiment analysis and text classification. Reference [6] introduces a novel text classification model, employing word2vec for word vector representation training and utilizing BiLSTM networks and CNN to capture contextual and thematic features. This model holds substantial relevance for the tourism industry, as it facilitates identifying and categorizing crucial information and sentiments within travel reviews, thereby assisting travel professionals in gaining a more profound understanding of customer feedback. Reference [7] uses a machine learning framework to extract sentiment and rating information from tourism reviews. This research is significant due to its demonstration of the high predictive accuracy of machine learning models in discerning emotions and ratings from visitor feedback, a critical aspect of customer satisfaction and market analysis within the tourism sector. In Reference [8], deep learning techniques are explored to address class imbalance issues in citation classification datasets through the application of focal loss and class weighting functions, thereby enhancing classification performance. The value of this research for the tourism industry lies in its capacity to identify tourism-related studies and literature through citation classification, thereby aiding researchers in better understanding industry trends.

In conclusion, these case studies underscore the importance of incorporating artificial intelligence sentiment analysis within the tourism industry. These technologies offer tourism professionals the means to deepen their comprehension of customer feedback, elevate service quality, conduct market analyses, and leverage research and literature more effectively. Whether leveraging word2vec, BiLSTM, CNN, or other technological resources, these studies have delivered invaluable tools and insights for the tourism sector, ultimately enhancing its competitiveness and efficiency.

Several scholars have made significant contributions to the advancement of neural networks in this field. Yu combined a neural network with Field-Programmable Gate Array (FPGA) convolution techniques to establish a predictive model for tourism demand. The findings of the study indicate that this approach enhances prediction accuracy compared to FPGA-only methodologies [9]. Adil et al. introduced a bidirectional long short-term memory neural network for tourist arrival prediction. In contrast to conventional LSTM networks, which preserve information in a unidirectional manner, the proposed BiLSTM network retains information in both left-to-right and right-to-left directions, thus enriching the model's contextual information [10].

This section discusses two case studies. One involves the fusion of neural networks with FPGA convolution technology for tourism demand prediction, while the other utilizes bidirectional long short-term memory neural networks for predicting tourist arrivals. These case studies highlight the pivotal role of neural networks and artificial intelligence in the tourism industry. Whether it pertains to demand forecasting through the incorporation of FPGA convolution technology or tourist arrival prediction via BiLSTM networks, these technologies significantly enhance the efficiency and precision of the tourism sector. They empower tourism professionals to more effectively address customer requirements, optimize resource allocation, and gain a competitive advantage. Hence, adopting artificial intelligence, particularly neural network technologies, is a pivotal factor in propelling the tourism industry towards success and progress.

The studies mentioned above have substantially enhanced the application of neural networks in the field of tourism. They cover a wide range of applications, including text classification, sentiment analysis, and tourist demand prediction. This multifaceted exploration provides strong support for the scope of this study. Smart tourism services epitomize an evolution in the tourism landscape underpinned by cutting-edge technology. With features ranging from intelligent navigation to tailor-made recommendations and real-time information dissemination, these services elevate the convenience and contentment of travelers throughout their journeys. Their impact reverberates not only in facilitating tourists' trip planning and enjoyment but also in affording the tourism sector enhanced operational efficiency, cost reduction, and a heightened competitive edge. In practical scenarios, the delivery of smart tourism services transpires through diverse avenues, encompassing smartphone applications, virtual tour companions, and the astute administration of tourist destinations. These services usher in personalized and user-friendly travel experiences while concurrently furnishing destination and service providers with the wherewithal to improve management and optimize resource allocation. This duality holds profound implications for tourist attraction, the sustainable advancement of the tourism domain, and the amplification of regional economic prosperity.

III. RESEARCH MODEL

A. CNNS

Convolution is a widely used mathematical operation that plays a crucial role in extracting features from different types of data, including one-dimensional time series, two-dimensional images, and higher-dimensional datasets [11]. It serves as a fundamental operation within CNNs. In the context of a continuous variable x, convolution is computed through integration, as illustrated in Equation (1).

$$h(x) = \int_{-\infty}^{\infty} f(\tau)\, g(x-\tau)\, d\tau \tag{1}$$

Consider two integrable functions, $f(x)$ and $g(x)$, defined on the real numbers, with x belonging to the real domain R. It is established that the integrals are well-defined for almost every real number x. The variability in outcomes arising from different values of x gives rise to the concept of convolution as a function $h(x)$ dependent on x. This convolution function symbolizes the convolution of functions f and g, and can be represented as shown in Equation (2).

$$h(x) = (f * g)(x) \tag{2}$$

Upon computation, it becomes clear that $(f * g)(x) = (g*f)(x)$, and remains $(f * g)(x)$ retains its status as an integrable function. The commutative property inherent in convolution is emphasized [12], [13], [14]. In cases where discrete data variables $f(x)$ and $g(x)$ are in use, discrete convolution can be formally defined as presented in Equation (3).

$$s(x) = (f * g)(x) = \sum\nolimits_{a=-\infty}^{\infty} f(a)\, g(x-a) \tag{3}$$

In Equation (3), $s(x)$ indicates discrete convolution, and a serves as a parameter. When conducting two-dimensional convolution of a kernel with a two-dimensional image, Equation (4) is derived.

$$S(i,j) = (I * K)(i,j) = \sum\nolimits_m \sum\nolimits_n I(m,n)\, K(i-m, i-n) \tag{4}$$

In Equation (4), i, j, m, and n denote distinct parameters. I represents the image, while K stands for the two-dimensional kernel [15], [16], [17]. By leveraging the commutative property of convolution, Equation (4) can alternatively be expressed as Equation (5).

$$S(i,j) = (K * I)(i,j) = \sum\nolimits_m \sum\nolimits_n I(i-m, i-n)\, K(m,n) \tag{5}$$

The cross-correlation function is often equated with convolution in practical machine learning implementations, as demonstrated in Equation (6).

$$S(i,j) = (K * I)(i,j) = \sum\nolimits_m \sum\nolimits_n I(i+m, i+n)\, K(m,n) \tag{6}$$

In Equation (6), I represents the image, while K denotes the two-dimensional kernel. $I(i+m, i+n)$ denotes the pixel value of the image I at position $(i+m, i+n)$, and $K(m,n)$ represents the weight value of the kernel K at position (m,n) In the convolution operation performed within matrices, the kernel K can be visualized as a sliding module traversing image I, with each position corresponding to a value. This value is obtained by summing the element-wise product of the kernel K and the elements within the enclosed matrix bordered in black [18]. The process of two-dimensional convolution is illustrated in Figure 1.

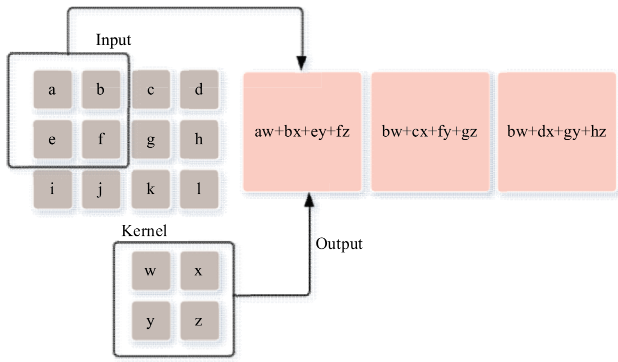

FIGURE 1. Process of two-dimensional convolution.

The convolution operation entails the manipulation of three key parameters: kernel size, stride, and padding. Employing multiple convolution kernels with consistent strides leads to the generation of multiple feature maps [19], [20], [21]. The kernel size k, representing the dimensions of the convolution kernel, is typically square. The resulting size after convolution is determined by Equation (7).

$$H_n = \frac{H_{n-1} - k + 2p}{s} + 1 \tag{7}$$

Here, H_n and H_{n-1} denote the input feature map size, s represents the stride, p signifies the padding, and k stands for the kernel size. CNNs, a prominent algorithm within the neural network domain, possess inherent feature learning capabilities, making them suitable for various tasks, such as computer vision, speech recognition, and text classification [22]. The fundamental process of sentiment classification using deep learning is illustrated in Figure 2.

In the realm of text data analysis, CNNs are employed to extract multi-level abstract features. A standard CNN architecture comprises key components, including convolutional, pooling, and fully connected layers [23]. The architecture of a Convolutional Neural Network typically includes input, convolutional, pooling, and fully connected layers, as illustrated in Figure 3.

Input Layer: In the CNN framework, this layer is responsible for the initial processing of the text to be classified. It introduces the classification features of the text into the model, creating the feature vector for the classified text, which serves as the model's input [24].

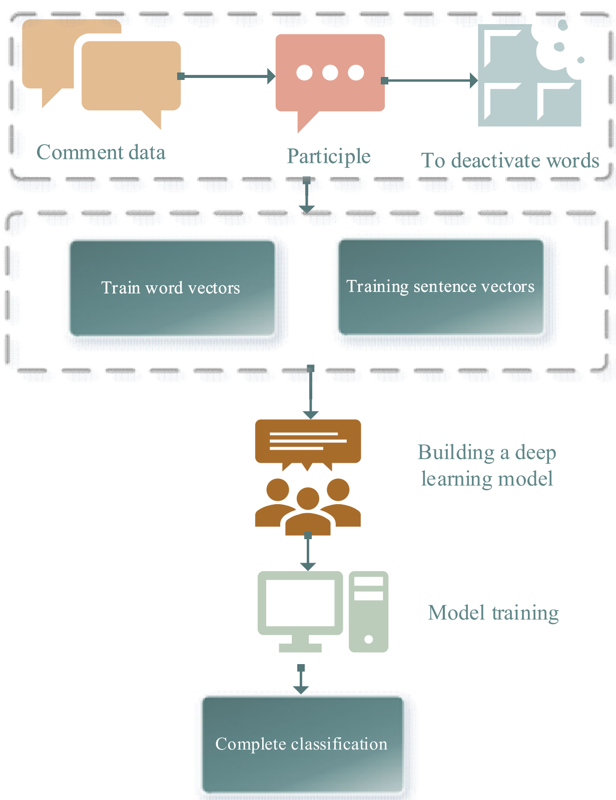

FIGURE 2. Basic process of deep learning to achieve emotion classification.

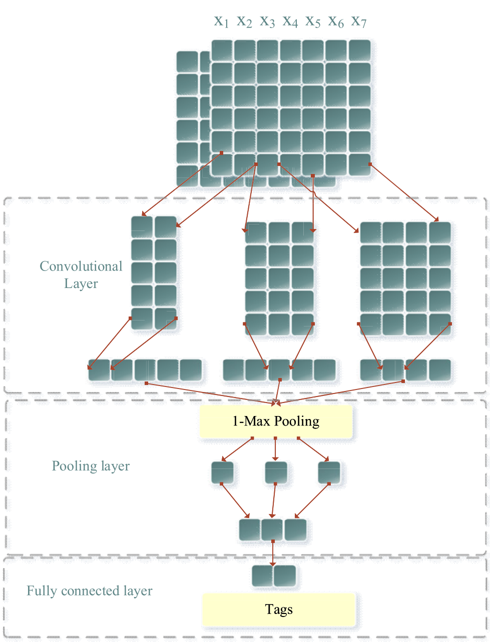

FIGURE 3. Architecture of CNN.

Convolution Layer: This phase involves multiple feature planes, each distributed across numerous neurons and connected to the matrix vector of the input layer through convolution kernels.

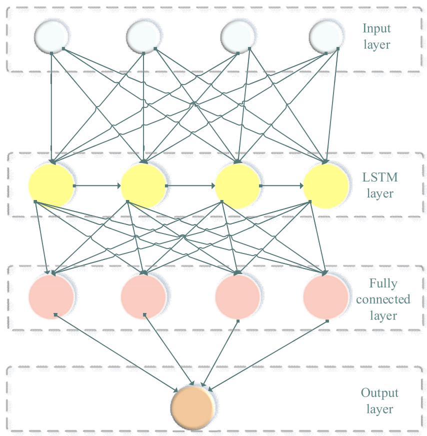

FIGURE 4. LSTM model structure.

Pooling Layer: After feature extraction is completed in the convolutional layer, the resulting feature map is subjected to processing in the pooling layer. The main purpose of the pooling layer is to reduce the size of the feature map, thereby compressing the data and improving the network's ability to generalize [25], [26], [27]. This layer is also known as the down-sampling layer. Prominent pooling methods include average pooling, maximum pooling, and global pooling.

Fully Connected Layer: Similar to the hidden layer in traditional feedforward neural networks, the fully connected layer operates on analogous principles and exhibits structural characteristics comparable to the output layer of input neural networks [28].

B. LONG SHORT-TERM MEMORY NEURAL NETWORK

Long Short-Term Memory (LSTM) networks, a subset of deep learning neural networks, are designed to address the vanishing gradient problem that arises with long input sequences [29]. In response to this challenge and with the goal of capturing intricate, long-range non-linear relationships comprehensively, researchers have explored various modifications to neural network architectures. This endeavor led to the integration of gated structures in the form of LSTMs, which proved effective in mitigating the vanishing gradient issue [30]. The LSTM model consists of four network layers, each serving a specific purpose within the architecture. Figure 4 illustrates the structure of the LSTM model.

Within the LSTM architecture components, the gate control units play a crucial role in regulating the retention and erasure of input data from previous time steps [31], [32]. The forget gate control plays a central role in selectively discarding irrelevant information. The mathematical calculation of the forget gate is explained by Equation (8).

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{8}$$

In the context of the activation function, the use of square brackets primarily serves to combine two vectors, with σ representing the sigmoid function, W_f denoting the weight parameter associated with the forget gate, and *Merge* $[h_{t-1}, x_t]$ indicating the combination of the variables h_{t-1} and h_{t-1} into a new variable [33]. Here, x_t corresponds to the bias term.

The purpose of the input gate is to calculate the relevant information from the current input x_t that requires retention, in conjunction with the newly generated state c_t. The corresponding computational expression is as follows:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{9}$$

$$\tilde{c}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_c) \tag{10}$$

$$c_t = f_t * c_{t-1} + i_t * \tilde{c}_t \tag{11}$$

Similar to the computation of f_t, the calculation of i_t follows a similar process; i_t represents the relevant retained information. Additionally, $\tilde{c}_t$ signifies the new state formed by combining the current and previous information. It is important to note that *tanh* serves as a non-linear activation function similar to sigmoid. Furthermore, c_t represents the combined information that represents the memory of the current moment [34]. The final output is obtained through the output gate following the cell operation, with the initial output expressed as formulated in Equation (12).

$$o_t = f(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{12}$$

According to the setup of the output gate, this result requires further filtering through the tanh function. As a result, the final output value at time t is determined by Equation (13).

$$h_t = o_t \cdot \tan(c_t) \tag{13}$$

In Equation (13), c_t signifies the cell state at the current time step, while o_t represents the weight proportion associated with the output information [35].

C. CONSTRUCTION OF SMART TOURISM TEXT CLASSIFICATION MODEL

This study combines the features of the CNN and the BiLSTM models to create a deep learning framework known as CNN-BiLSTM. This model is tailored for the classification of tourists' emotions. The model's architecture is visually represented in Figure 5.

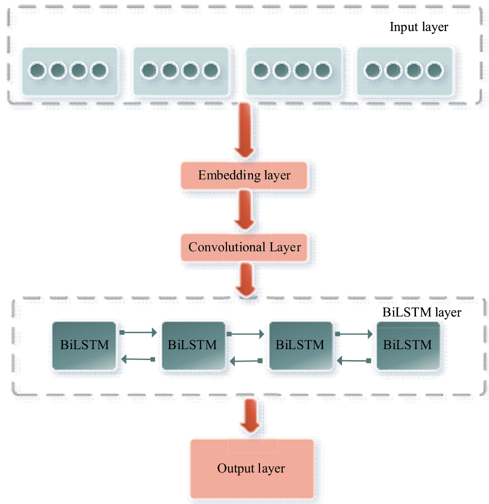

FIGURE 5. Structure of the CNN-BiLSTM model.

D. WEB CRAWLED TOURISM TEXT DATA

This study collects a subset of tourist attraction reviews from Ctrip.com, serving as the primary data source. The use of web crawling technology, a contemporary method for acquiring experimental data in text mining, not only streamlines data collection but also establishes the foundation for subsequent research efforts [36], [37], [38]. The process of extracting tourist attraction review information is illustrated in Figure 6.

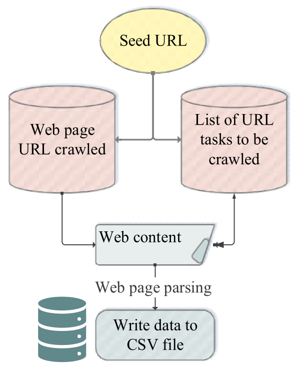

FIGURE 6. IlLustration of the process for extracting attraction review information through web crawling.

The main objective of the crawler is to collect textual content from tourist attraction reviews. The crawling process unfolds in several stages. In the initial phase, the targeted content is defined, the Uniform Resource Locator (URL) for crawling is specified, and the seed URL is extracted from the website's source code. This seed URL is then added to the URL task queue for crawling. Subsequently, using Python's versatile crawler libraries, such as urllib and requests, the process simulates a browser-like request sent to the server. In the next phase, after obtaining the target URL, the process begins extracting valuable data from the website [7], [39], [40]. This extraction is facilitated through the use of regular expressions to parse tourist attraction review text data embedded within web pages. The third stage involves the extraction of relevant information, a crucial phase in the crawling process essential for obtaining meaningful results [41]. This involves extracting valuable and coherent data from extensive and disorganized information sources [42]. The final stage involves data storage. Given the substantial volume of tourist attraction review text data collected in this study, totaling 110,000 records, the decision was made to store it in an xlsx file format for easy management and accessibility.

When calculating communication and computation costs, several critical factors come into play: (1) data transfer volume: estimating the size of the data being transmitted is essential; (2) data transfer speed: knowledge of the data transfer speed, typically measured in bits per second (bps), is imperative; (3) transfer time: calculating the time needed for transmission, a unit typically expressed in seconds; (4) communication equipment costs: this category covers expenses related to equipment used for data transmission, encompassing servers, routers, and network bandwidth; (5) Transmission protocols: the choice of transmission protocol can have varying cost implications and, thus, necessitates careful consideration. In the realm of cost calculations, additional factors include: (1) compute resource usage: identifying the computational resources in play, including Central Processing Unit, Graphics Processing Unit, and memory; (2) computation time: grasping the time required for computations, typically denominated in seconds; (3) computing equipment costs: this category includes outlays linked to equipment employed for computations, such as servers and cloud computing instances; (4) computational algorithm efficiency: different algorithms may lead to differing costs even when utilizing the same computational resources. This implies the need for thoughtful selection.

IV. EXPERIMENTAL DESIGN AND PERFORMANCE EVALUATION

A. DATASETS COLLECTION

This study systematically organizes the URLs of each scenic spot's respective pages on Ctrip, acquiring page link information from a total of 92 scenic spots. These gathered URLs are then input into a specialized web crawler, where data collection rules are carefully defined, considering the review pages' unique layouts and characteristics. Through this strategic approach, the collection of tourist review data is efficiently achieved. However, the potential existence of invalid data within the crawled tourist reviews raises concerns about its impact on subsequent experimental results, necessitating a proactive course of action.

A meticulous process of filtering out these inaccurate reviews from the gathered tourist review data is carried out to address this issue. Since this study aims to create a model for classifying tourist emotions, it is crucial to classify all review data into positive or negative emotional categories. Given the extensive amount of comment data, a judicious strategy is employed to associate ratings with sentiment labels.

In particular, comments with ratings of 4 or 5 are labeled as positive, those with ratings of 1 or 2 are categorized as negative, and comments with a rating of 0 or 3 are also considered negative. Manual evaluation is utilized for this classification procedure to guarantee accuracy by carefully assigning labels to each review data point. After these thorough processes, a total of 28,127 tourist comments were successfully obtained. Within this dataset, an impressive 24,116 are classified as positive comments, while 4,011 are labeled as negative comments.

B. EXPERIMENTAL ENVIRONMENT AND PARAMETERS SETTING

To enhance model performance, a systematic exploration of parameter configurations is conducted using the Grid-Search Cross-Validation method, an essential component of Python's sklearn library. This approach facilitates meticulous adjustments within both the convolutional and BiLSTM layers, culminating in identifying an optimal parameter amalgamation.

The resulting configuration, carefully optimized, includes the following key settings: In the CNN layer, a set of 64 convolutional filters is defined, each with a filter size of 3 and operating with a stride of 1. Simultaneously, the BiLSTM layer is equipped with 50 units and a prudent dropout rate of 0.2, promoting model robustness. The refinement process also extended to training parameters, with thoughtful decisions guiding their specification. A batch size of 64 training samples per batch and an extensive training regimen of 20 iterations are considered optimal. This rigorous parameter optimization has produced a finely-tuned model configuration poised to deliver improved performance results.

C. PERFORMANCE EVALUATION

The effectiveness of the model proposed in this study is assessed using a set of rigorous criteria, which includes the accuracy rate, precision rate, recall, and the Macro F1 value. Of these metrics, the accuracy rate holds significant importance, as it quantifies the proportion of correctly predicted samples in relation to the total dataset size. The accuracy rate is mathematically calculated as shown in Equation (14).

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{14}$$

In Equation (14), TP represents the number of true positive samples that the model accurately classifies as positive, while TN stands for the number of true negative samples that the model accurately classifies as negative. Conversely, FP indicates the number of false positive samples that the model erroneously classifies as positive, and FN designates the number of false negative samples that the model inaccurately classifies as negative. Precision quantifies the ratio of correctly categorized positive samples to the total number of samples predicted as positive by the classifier. This metric provides valuable insights into the model's predictive precision, and its calculation is outlined in Equation (15).

$$\text{Precision} = \frac{TP}{TP + FP} \tag{15}$$

Recall, often referred to as sensitivity, measures the proportion of accurately classified positive samples in relation to the total number of actual positive samples. This metric primarily represents the ratio of predicted positive instances within the actual positive instances, indicating the model's ability to effectively capture positive instances. The mathematical expression for recall is presented in Equation (16).

$$\text{Recall} = \frac{TP}{TP + FN} \tag{16}$$

Precision and recall are interconnected evaluation metrics often exhibiting an inverse relationship. Higher precision typically coincides with lower recall, while increased recall often corresponds to lower precision, indicating a trade-off between the two. In contrast, the Macro F1 value, considered their harmonic mean, serves as a balanced metric that considers both precision and recall. Its calculation is governed by Equation (17).

$$\mathrm{F1} = \frac{2 * Precision * Recall}{Precision + Recall} \tag{17}$$

To thoroughly evaluate the effectiveness of the CNN-BiLSTM model, this study conducts rigorous comparative experiments involving the BiLSTM model and the Text Convolutional Neural Network (TextCNN) model. The objective is to assess the classification capabilities of these three models, with a specific focus on positive comments, using the test dataset. The classification performance of all three models is illustrated in Figure 7.

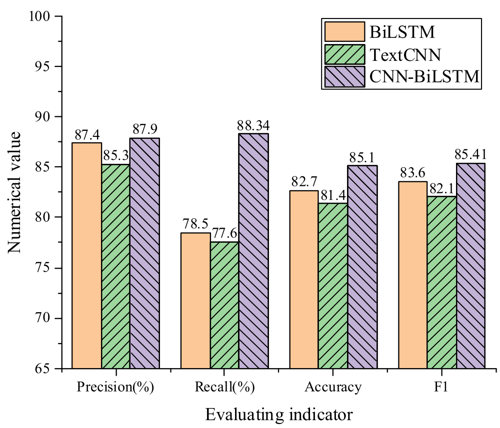

FIGURE 7. Classification performance of three models on positive reviews within the test set.

The apparent trends in the data emphasize the disparities observed among the three models across various evaluation metrics. Concerning accuracy, the CNN-BiLSTM model exhibits the highest performance, achieving an impressive 87.9%. Following closely, the BiLSTM model attains an accuracy of 87.4%, while the TextCNN model slightly lags behind at 85.3%. Shifting to recall rates, the CNN-BiLSTM model consistently showcases its proficiency by reaching an impressive 88.34%. In contrast, the BiLSTM and TextCNN models achieve recall rates of 78.5% and 77.6%, respectively.

The CNN-BiLSTM model maintains its prominent position in terms of accuracy metrics, achieving an impressive rate of 85.1%. In comparison, the BiLSTM and TextCNN models reach accuracy rates of 82.7% and 81.4%, respectively. When considering the F1 values, the CNN-BiLSTM model outperforms its counterparts with a value of 85.41%. Conversely, the BiLSTM and TextCNN models attain F1 values of 83.6% and 82.1%, respectively. The following section presents the classification performance of these three models when addressing negative reviews within the test dataset, as illustrated in Figure 8.

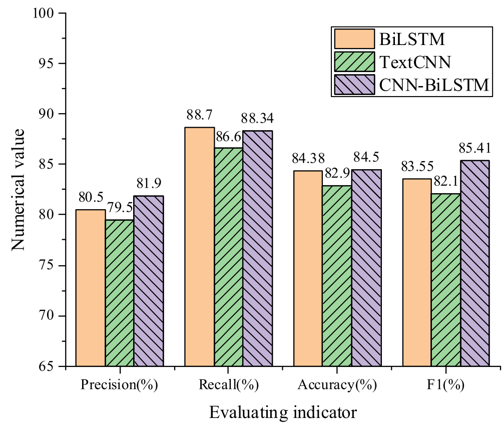

FIGURE 8. Classification performance of three models on the test set for negative reviews.

The discernible differences in classification performance among the three models for negative comments are prominently illustrated in Figure 8. When considering precision, it is noteworthy that the CNN-BiLSTM model stands out as the top performer with an impressive score of 81.9%, closely followed by the BiLSTM model at 80.5%, and the TextCNN model at 79.5%. A recall assessment indicates that the CNN-BiLSTM and BiLSTM models demonstrate comparable effectiveness, achieving recall rates of 88.34% and 88.7%, respectively. In contrast, the TextCNN model lags slightly behind with a recall rate of 86.6%.

When evaluating the accuracy, the CNN-BiLSTM model consistently emerges as the leader, achieving an impressive accuracy rate of 84.5%. The BiLSTM and TextCNN models closely follow with accuracy levels of 84.38% and 82.9%, respectively. Lastly, in terms of the F1 score, the CNN-BiLSTM model outperforms its counterparts, exhibiting a value of 85.41%. The BiLSTM model also delivers a commendable performance with an F1 score of 83.55%, while the TextCNN model lags slightly behind with an F1 score of 82.1%. These data-driven findings unequivocally emphasize the superior performance of the CNN-BiLSTM model across various evaluation metrics in the challenging task of classifying negative comments, underscoring its distinct advantage in this particular domain.

Loss functions are utilized to gauge the disparity between the model's predicted outcomes and actual data, where smaller loss function values denote improved model performance. In the experiments conducted in this paper, three distinct models were compared. To facilitate a lucid evaluation of their classification effectiveness, a confusion matrix served as the evaluative tool. The aggregate sample size consisted of 9,782 instances, among which 7,234 samples represented a true positive sentiment, while 2,548 samples indicated a true negative sentiment. An analysis of the confusion matrix results yielded the following insights: the models effectively predicted 6,986 instances characterized by positive sentiment and 2,384 instances associated with negative sentiment. These observations underscore the exceptional precision and accuracy of the proposed sentiment classification model, operating based on textual analyses of travel reviews. The model attains a commendable precision rate of 95.79%. In contrast to alternative sentiment classification models applied to travel-related texts, this model demonstrates a significant enhancement in performance.

D. DISCUSSION

This study seeks to improve information management within smart tourism IoT services by incorporating a CNN text classification algorithm. It rigorously compares three deep learning models – BiLSTM, TextCNN, and CNN-BiLSTM – in the context of emotion classification tasks through systematic experiments. The subsequent discussion explores the experimental results, their significance for enhancing smart tourism IoT services, and potential avenues for future research.

The experimental results support the CNN-BiLSTM model, which demonstrates exceptional performance across a range of evaluation metrics. Its remarkable precision and recall underscore its proficiency in discerning and categorizing emotional sentiment within user reviews, presenting valuable insights for information management in smart tourism IoT services. Precise sentiment analysis can enhance companies' understanding of user sentiments and opinions, facilitating timely and targeted improvements. By harnessing the effectiveness of the CNN-BiLSTM model, businesses can make well-informed decisions, enhance user experiences, and elevate satisfaction levels within smart tourism IoT services.

In summary, this study makes a substantial contribution to sentiment analysis within smart tourism IoT services, highlighting the effectiveness of the CNN-BiLSTM model. The results underscore its capacity to enhance information management strategies and user engagement in the ever-changing landscape of tourism services. As this field advances, ongoing exploration of deep learning techniques holds the promise of further developing sophisticated sentiment analysis methods and customer-focused solutions.

Moreover, improved precision and recall rates play a crucial role in enriching user experiences by offering accurate, tailored recommendations and suggestions. This enhancement, in turn, promotes the evolution of smart tourism services. Providing precise recommendations nurtures user trust and encourages active participation in smart tourism IoT services, enhancing user satisfaction and fostering loyalty. In summary, the empirical results underscore the outstanding effectiveness of the CNN-BiLSTM model in sentiment classification tasks.

The case studies presented here aim to enhance information management and user sentiment analysis in smart tourism IoT services by utilizing deep learning techniques, specifically the CNN-BiLSTM model. These experimental results strongly support the superior performance of this approach in sentiment classification tasks, highlighting its proficiency in identifying and categorizing sentiment polarity in user reviews. This achievement carries significant implications for information management in smart tourism IoT services. Accurate sentiment analysis assists companies in comprehending user opinions and emotions, enabling more timely and precise service optimization. Furthermore, our research contributes to improving user experiences, bolstering trust and loyalty toward smart tourism services, and ultimately increasing satisfaction by delivering precise, personalized recommendations. In summary, this study offers effective information management strategies for smart tourism services and paves the way for future research, particularly in the context of the ongoing development of deep learning technologies. This promises more refined sentiment analysis methods and user-engaged solutions for the tourism industry. This study is anticipated to drive further advancements in smart tourism services, enhancing their practical applications and overall user experience.

The previous experiments compared three deep learning models: BiLSTM, TextCNN, and CNN-BiLSTM. The CNN-BiLSTM model demonstrated a significant performance improvement compared to existing methods, which positively impacts the information management of smart tourism IoT services. Firstly, precise sentiment analysis assists businesses in gaining a deeper understanding of user opinions and sentiment tendencies. This improvement enables companies to make more timely and targeted optimizations and adjustments to meet user needs, ultimately enhancing user satisfaction. Moreover, high accuracy and recall rates also enhance the user experience by providing more precise personalized recommendations and suggestions. This result, in turn, further promotes the enhancement of smart tourism services. Users stand to benefit from more precise recommendations and suggestions, increasing their inclination to use and trust smart tourism IoT services, thereby enhancing overall user satisfaction and loyalty.

V. CONCLUSION

A. RESEARCH CONTRIBUTION

This study aims to explore and introduce a convolutional neural text classification algorithm to enhance information management in smart tourism IoT services. In this context, the study offers significant contributions to information management within the domain of smart tourism:

This study introduces, for the first time, deep learning algorithms that include CNNs and BiLSTM networks. Their innovative utilization strengthens text sentiment classification tasks within the domain of smart tourism IoT services. These advanced algorithms enable a more precise understanding of emotional nuances within user reviews, thus providing substantial support for the improvement of smart tourism services.

The research findings presented here provide practical insights for implementing information management in the context of smart tourism IoT services. Through sentiment analysis, companies operating in the realm of smart tourism can attain a deeper understanding of user feedback and emotional cues, enabling them to fine-tune their services, enhance products, and ultimately increase user satisfaction. This, in turn, has a positive impact on the sustainable advancement of the smart tourism sector. In summary, this study introduces an advanced convolutional neural text classification algorithm to the field of information management in smart tourism IoT services. Through performance evaluation and advocacy for practical application, this contribution significantly enriches the sector's development and fosters innovation.

This study makes several significant scientific contributions:

1. Introduction of Deep Learning Technology: The study introduces deep learning technologies, specifically CNN and BiLSTM, within the context of smart tourism. This introduces a new technological paradigm to traditional tourism business management, with the potential to enhance the efficiency of processing and analyzing tourism data.

2. Practical Application of Sentiment Analysis: The study applies deep learning techniques to sentiment analysis to identify sentiment tendencies in customer reviews and feedback. This equips tourism businesses with tools to better comprehend customer satisfaction, emotional responses, and needs, thereby improving service quality.

3. Novel Model: The study extensively discusses the utilization of the CNN-BiLSTM text classification model, showcasing innovation in handling text data in the smart tourism domain. The study underscores its superiority in sentiment analysis and text processing through a performance analysis of the model.

4. Informatization Management of Smart Tourism Business: The study highlights the fusion of deep learning technology and sentiment analysis, presenting a viable solution for the informatization management of smart tourism services. This can potentially drive informatization management within the tourism industry, offering tourism businesses increased opportunities and a competitive edge.

In summary, this study leverages deep learning technology within the realm of smart tourism, specifically focusing on sentiment analysis, and offers a substantial scientific contribution. It introduces novel management tools for the smart tourism industry, potentially elevating customer experiences, service quality, and laying a robust foundation for information management and innovation in the tourism sector.

B. FUTURE WORKS AND RESEARCH LIMITATIONS

Despite the remarkable performance of the CNN-BiLSTM model in this study, several avenues warrant comprehensive exploration. To begin, the incorporation of multimodal data offers an opportunity to enhance the sources of information used in sentiment analysis. This integration could encompass diverse data types, including text, images, and audio, thereby enabling a comprehensive analysis. Such an approach would closely align with users' authentic emotional expressions, providing a more comprehensive framework for improving smart tourism services. Furthermore, the adaptability of sentiment analysis across different tourism contexts is a critical consideration. Various tourism scenarios may give rise to diverse emotional nuances, necessitating model optimization and customization tailored to specific contexts. Lastly, the realm of cross-lingual and cross-domain sentiment analysis presents a promising avenue for future research. Given the global reach and diversified nature of contemporary tourism services, sentiment analysis spanning different languages and domains assumes paramount significance. Researchers are encouraged to explore strategies for adapting models to varying languages or domains, with the goal of facilitating broader and more versatile applications.

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