J. Electrical Systems 20-2s (2024): 233-240

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Utilizing BiLSTM For Fine-Grained Aspect-Based Travel Recommendations Using Travel Reviews In Low Resourced Language

Abstract: - Recommender systems have become an essential tool for enhancing user experiences by providing personalized recommendations. In this study, we present a novel approach to constructing a recommender system specifically tailored for Malayalam travel reviews. Our objective was to extract relevant features from these reviews and employ a bidirectional Long Short-Term Memory (BiLSTM) architecture to construct a robust and accurate recommendation model. We focused on four key features extracted from the travel reviews: travel mode, travel type, location climate, and location type. The travel mode feature encompassed the mode of transport opted for the travel such as bus, car, train, etc., while the travel type captured the nature of the trip, including family, friends, or solo travel. Additionally, we considered the climate of the location, including rainy, snowy, hot, and dry, among others, and the location type, such as beach, hilly, or forest destinations. To construct our recommender system, we implemented a BiLSTM architecture, a powerful deep-learning model known for effectively capturing temporal dependencies in sequential data. This architecture allowed us to process the extracted features and learn the underlying patterns within the Malayalam travel reviews. Our experiments were conducted on a comprehensive dataset of Malayalam travel reviews, carefully curated for this study. The dataset encompassed a diverse range of travel experiences, enabling our model to learn from a wide variety of user preferences and recommendations. The performance evaluation of our recommender system yielded promising results. With an accuracy of 83.65 percent, our model showcased its ability to accurately predict and recommend travel options based on the extracted features from the reviews. The high accuracy achieved by our model underscores the effectiveness of the BiLSTM architecture in capturing the nuances of the Malayalam language and understanding the subtle preferences expressed in travel reviews. The practical implications of our work are significant, as it offers a valuable tool for travelers seeking personalized recommendations based on their travel preferences. The use of the Malayalam language in this context expands the reach of recommender systems to a wider audience, catering specifically to individuals who prefer to consume content and make decisions in their native language.

Keywords: Travel Recommender System, Natural Language Processing, BiLSTM, Malayalam.

I. INTRODUCTION

In recent years, recommender systems have emerged as crucial tools for providing personalized recommendations and enhancing user experiences in various domains. The travel industry is no exception, with an increasing demand for tailored travel recommendations based on user preferences. However, most existing recommender systems are designed for English or other widely spoken languages, leaving a gap in catering to specific linguistic communities. This work focuses on addressing this gap by developing a recommender system specifically tailored for Malayalam travel reviews. Malayalam is a Dravidian language predominantly spoken in the Indian state of Kerala and neighboring regions. By leveraging the unique features and characteristics of Malayalam travel reviews, we aim to provide accurate and personalized travel recommendations to Malayalam-speaking users.

To achieve this goal, we extracted four key features from the travel reviews: travel mode, travel type, location climate, and location type. The BiLSTM model enables us to process the extracted features from the Malayalam travel reviews and learn intricate patterns and relationships that influence user preferences.By leveraging a carefully curated dataset of Malayalam travel reviews, we trained and evaluated our recommender system. The dataset encompasses a wide range of travel experiences, providing a diverse set of preferences and recommendations to learn from. Through rigorous experimentation and evaluation, we assessed the performance of our model in accurately predicting and recommending travel options based on the extracted features.The results of our study demonstrated a commendable accuracy of 83.65 percent for our recommender system. This high accuracy underscores the efficacy of the BiLSTM architecture in capturing the unique nuances of the Malayalam language and comprehending the subtle preferences expressed in travel reviews. The success of our approach offers a promising solution for personalized travel recommendations to Malayalam-speaking users, improving their travel planning and decision-making processes.

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The contributions of this work are not limited to the field of recommender systems. By tailoring our model specifically to Malayalam travel reviews, we extend the reach of recommender systems to linguistic communities that prefer consuming content and making decisions in their native language. This not only enhances the user experience but also promotes cultural inclusivity and diversity in the digital travel space. The following sections will delve into the methodology, experiments, and results in detail, highlighting the significance and implications of our work for both the recommender systems and the Malayalam-speaking travel community.

Key Contributions:

1. Tailored Recommender System for Malayalam Travel Reviews. By considering the unique features and characteristics of the language, the model offers accurate and relevant recommendations to Malayalam-speaking users.
2. Feature Extraction: The study identifies and extracts four key features from the Malayalam travel reviews, including travel mode, travel type, location climate, and location type. These features capture crucial aspects that influence travel preferences and allow the recommender system to understand and incorporate user-specific requirements.
3. Bidirectional Long Short-Term Memory (BiLSTM) Architecture: By employing BiLSTM deep learning architecture, the model can process and analyze the extracted features, enabling it to learn intricate patterns and relationships within the Malayalam travel reviews.
4. Dataset Curation: The carefully curated dataset encompasses a diverse range of travel experiences, ensuring that the recommender system learns from a wide variety of user preferences and recommendations, thereby enhancing its accuracy and robustness.
5. High Accuracy: The experimental evaluation of the recommender system demonstrates an impressive accuracy of 83.65 percent. This indicates the model's ability to accurately predict and recommend travel options based on the extracted features from the Malayalam travel reviews, thus showcasing its effectiveness in meeting user expectations.
6. Language Inclusivity: By tailoring the recommender system specifically to Malayalam travel reviews, this work promotes linguistic inclusivity in the digital travel space and enhancing their travel planning experiences and catering to their specific cultural and linguistic preferences.

Overall, this study makes significant contributions to the field of recommender systems by providing a tailored solution for Malayalam travel reviews. The work not only improves the travel experiences of Malayalam-speaking users but also sets a precedent for developing recommender systems for other regional languages, contributing to the broader goal of linguistic and cultural inclusivity in recommendation technologies.

II. LITERATURE REVIEW

Ilham Safeek proposed a method for recommending career paths to users based on their Facebook data. The method first extract features from the user's Facebook data, such as their posts, engagements, and sentiments [1]. Sunita Tiwari et al. proposed a method for improving the accuracy of recommender systems by processing data generated from Twitter. The method first extract features from Twitter data, such as the user's tweets, retweets, and likes [2]. A deep-level tagger for Malayalam has been implemented using word embedding and Support Vector Machine algorithms [3].

Yahya and Team proposed a multi-criteria decision-making method based on deep encoder to study the nonlinear relation between users. They also proposed a Correlation Coefficient and Standard Deviation approach to measure the nonlinear relation [4]. Elankath investigated the effectiveness of a pre-trained deep learning model in accurately analysing the underlying sentiments expressed in Malayalam texts. By focusing on sentiment analysis, the research seeks to uncover and understand the emotional aspects conveyed within Malayalam text data [5]. In paper [6] Yoon presented an innovative real-time recommenda- tion system for tourism, named R2Tour, designed to adapt to dynamic scenarios, including external factors and distance information, providing personalized recommendations for tourists based on their preferences and characteristics.

Paper [7] proposes a novel approach that leverages deep learning techniques within the context of global information management to provide personalized travel recommendations for different users by utilizing deep learning models and the system can effectively analyse and interpret large-scale global information, including user preferences, location data, and cultural factors, to generate tailored recommendations. Mahadevaswamy proposed a technical overview of a Bidirectional LSTM network for Sentiment Analysis. The proposed model effectively addressed the challenge of capturing long-term dependencies in sequential data by incorporating memory mechanisms, leading to improved prediction capabilities [8]. In paper [9] proposed a model with a combination of

Bidirectional Long Short-Term Memory (LSTM) and a Hierarchical Attention Mechanism. The proposed network architecture takes advantage of the strengths of both models to enhance the performance of sequence-based tasks.

III. DATASET

Facebook, being a prominent social media platform, serves as a crucial data source for various recommender systems aimed at predicting new suggestions and establishing customer relationships. Users from around the globe actively engage in numerous groups and pages to express their viewpoints and share experiences. In the context of Malayalam language, the largest Facebook travel group known as "Sanchari" serves as a hub for travel enthusiasts, boasting a membership of 700,000 individuals worldwide. This vibrant community actively participates in sharing their travel experiences, resulting in a collection of over 50,000 travelogues, each receiving hundreds of reactions. As an initial step, a customized scraping tool was employed to extract a dataset of 11,500 travelogues from the group, providing a valuable resource for further analysis and exploration.

IV. METHODOLOGY

The methodology of the proposed work involves the following phases as shown in Figure 1.

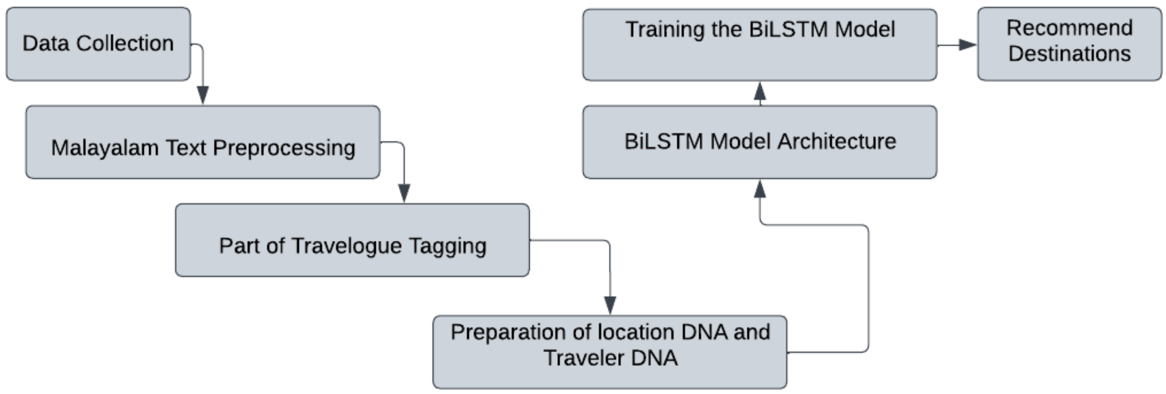

Figure 1. The steps involved in the proposed methodology.

4.1 Data Collection

The data extraction process in this study follows a three-step scraping algorithm to extract pertinent information from the source. Initially, the algorithm targets the posts and retrieves multiple attributes such as the Malayalam messages, posting time, reactions count, comments count, shares count, and author's profile URL for each post. Notably, the focus at this stage is not on extracting comments. In the subsequent step, the algorithm collects public personal details from the author's profile URL. These details include information like education, hometown, marital and family status, age, and check-in data. The data is obtained in JSON format and subsequently transformed into an Excel sheet, which constitutes the third and final stage of the scraping process. By employing this comprehensive approach, the algorithm effectively extracts and organizes relevant raw data, facilitating further analysis and exploration of the acquired information.

4.2 Malayalam Text Preprocessing

In this phase, several crucial tasks were undertaken to preprocess the data effectively. The primary objectives included removing non-Malayalam words, eliminating punctuation marks and HTML tags, and performing tokenization at both the sentence and word levels. Additionally, the removal of stop words was carried out to streamline the dataset further. To facilitate the extraction of root words, a Python package called "root_pack" was employed. This package played a vital role in determining the root forms of the words, contributing to a more accurate analysis of the text data. Overall, these preprocessing tasks significantly enhanced the quality and relevance of the data, preparing it for subsequent analysis and modeling. By removing irrelevant words, eliminating unnecessary symbols and tags, and extracting root words, the dataset became more refined and conducive to extracting meaningful insights.

4.3 Part of Travelogue Tagging

To overcome the absence of a suitable tagger for annotating Malayalam travel text, a novel tagger was developed in this study. This tagger, named the Part of Travelogue tagger (POT), was specifically designed to address the unique requirements of annotating travel-related details. By incorporating additional fields and tags into the existing Part of Speech tagger for Malayalam, the POT tagger enables precise and comprehensive annotation of text in the travel domain.

The development of the POT tagger fills a significant gap in the annotation tools available for Malayalam travel text. With its tailored set of tags, the POT tagger enhances the accuracy and specificity of annotations, facilitating deeper analysis and understanding of travel-related information. By extending the functionality of the existing Part of Speech tagger, the POT tagger ensures that essential details relevant to the travel domain are captured and annotated appropriately.

The integration of additional fields and tags in the POT tagger offers a more comprehensive approach to annotating travel text in Malayalam. It allows researchers and practitioners to annotate specific travel-related aspects, such as locations, transportation modes, travel activities, and other pertinent details. This fine-grained annotation capability is instrumental in extracting valuable insights and facilitating advanced natural language processing tasks tailored to the travel domain. In summary, the development of the Part of Travelogue tagger (POT) addresses the lack of an appropriate tagger for annotating Malayalam travel text. By extending the existing Part of Speech tagger with additional fields and tags, the POT tagger enables accurate and comprehensive annotation of travel-related details. This contribution enhances the analysis and understanding of Malayalam travel text, empowering researchers and practitioners in the travel domain with a valuable tool for deeper insights and more sophisticated natural language processing applications.

4.4 Preparation of location DNA and Traveler DNA

Within the realm of travelogues, an important feature called Travel DNA plays a pivotal role in capturing essential information. In this study, the POT Tagger is employed to process and annotate the descriptive write-ups from the dataset, emphasizing the most important tags associated with each domain. These tags, including Location, Travel Mode, Travel Type, Location Climate, and Type of Location, serve as the fundamental components that constitute the Travel DNA for each travelogue. The utilization of the POT Tagger enables a comprehensive analysis of the travelogues by accurately identifying and tagging crucial elements within the text. By annotating the write-ups with the relevant tags, the Travel DNA can be effectively extracted and quantified, providing valuable insights into various aspects of the travel experiences being described.The identified tags are specifically designed to capture significant details related to the travel domain. The Location tag identifies the specific geographic locations mentioned in the travelogues, enabling a deeper understanding of the destinations visited. The Travel Mode tag indicates the mode of transportation used during the travel, providing insights into the logistics and experiences associated with different modes of travel. The Travel Type tag classifies the nature of the trip, whether it was with family, friends, or solo, shedding light on the social context of the travel experience. The Location Climate tag identifies the prevailing climatic conditions during the travel, allowing for an exploration of the influence of weather on the overall experience. Finally, the Type of Location tag categorizes the nature of the destination, such as beach, hilly, or forest locations, providing insights into the diverse settings explored by the travelers.

By using the POT Tagger and annotating the descriptive write-ups with these crucial tags, the Travel DNA is constructed, offering a comprehensive representation of the key components that define each travelogue. This approach facilitates a deeper analysis and understanding of the travel experiences documented in the dataset, enabling researchers and practitioners to uncover patterns, preferences, and trends within the domain of travel. Table 1 describes structured feature set extracted from Malayalam travelogues with essential tags based on POT Tagger.

Table 1 The sample set of features extracted from different travellogues

Sl. No	Climate	Travel_type	Location_type	Travel_mode	Locations
1	മഴ	തനിയെ	സാഹസികം	കാർ	മണാലി
2	വെയിൽ	സോളോ	സിറ്റി	ബസ്	ദൽഹി
3	മഞ്ഞ്	കുടുംബം	ഹൈറേഞ്ച്	ബൈക്ക്	ഇടുക്കി
4	തണുപ്പ്	കൂട്ടുകാർ	സിറ്റി	തീവണ്ടി	കോഴിക്കോട്
5	ചൂട്	ഫ്രണ്ട്സ്	പ്രകൃതി	വിമാനം	കശ്മീർ
6	സമ്മർ	ചങ്ങാതി	സാഹസികം	ഫ്ലൈറ്റ്	ലഡാക്ക്
7	വിന്റർ	സഹപ്രവർത്തകർ	പ്രകൃതി	കപ്പൽ	കോവളം
7	ശൈത്യം	ഓഫീസ്	സാഹസികം	റോഡ്	ഗോവ
8	വസന്തം	ഭാര്യ	ഹൈറേഞ്ച്	കടൽ	വയനാട്
9	മഴ	ഭർത്താവ്	ചരിത്രം	ബോട്ട്	കാസർഗോഡ്
10	വെയിൽ	സഹോദരങ്ങൾ	പ്രകൃതി	സൈക്കിൾ	ആലപ്പുഴ
11	മഞ്ഞ്	അമ്മ	സിറ്റി	നടന്ന്	ബാംഗ്ലൂർ
12	തണുപ്പ്	അച്ഛൻ	തീർത്ഥാടനം	സ്കൂട്ടർ	മൈസൂർ

In the context of travelogues, as shown in Figure 2, Travel DNA represents a significant feature that captures essential information. By utilizing the POT Tagger, the descriptive writeups from the dataset are processed and annotated, highlighting the most crucial tags related to each domain. These tags, such as Location, Travel Mode, Travel Type, Location climate, and Type of Location, form the fundamental components of the Travel DNA for each travelogue.

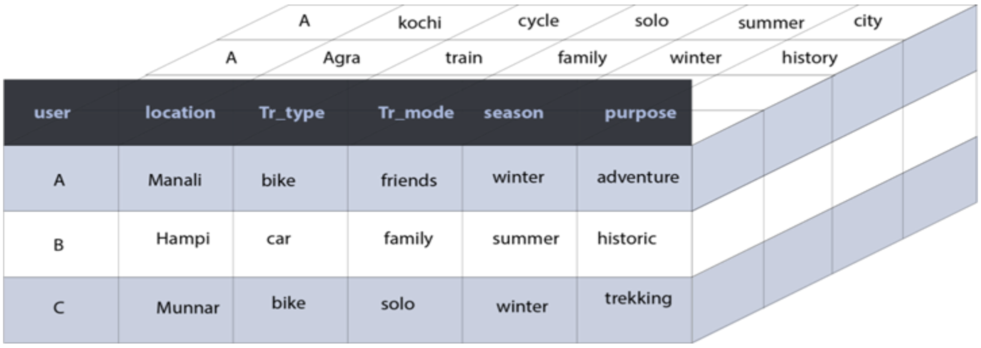

Figure 2. The Travel DNA

4.5 BiLSTM Model Architecture

The BiLSTM section of the experiment played a crucial role in constructing the recommender system for Malayalam travel reviews. The Bidirectional Long Short-Term Memory (BiLSTM) architecture selected due to its ability to capture and analyze sequential data, making it well-suited for processing the textual nature of travel reviews.

4.5.1 Input Encoding

The input to the BiLSTM model consisted of the preprocessed and feature-extracted dataset. Each travel review, represented as a sequence of words, was encoded into numerical representations to facilitate model training. This encoding was achieved by employing one-hot encoding to the feature set/travel DNA of each user.

4.5.2 BiLSTM Layer

The BiLSTM layer formed the core component of the model. It consisted of two LSTM (Long Short-Term Memory) networks, one processing the sequence in the forward direction and the other in the backward direction. This bidirectional nature allowed the model to capture both past and future contextual information for each word in the review. By considering the sequential dependencies in both directions, the BiLSTM effectively learned the underlying patterns and relationships within the travel reviews. Here we have an input sequence of length four which can be denoted by T, represented as $x = (x_1, x_2, x_3, x_4)$, where each x_i represents the input at time step i.The forward LSTM computes the hidden states $h^{t(0)}$ and cell states $c^{t(0)}$ using the forward propagation equations:

$$h^{t(0)} = \text{LSTM\_forward}(x^t, h^{t-1(0)}, c^{t-1(0)})\ c^{t(0)} = \text{LSTM\_ forward\_cell}(x^t, h^{t-1(0)}, c^{t-1(0)}) \quad (1)$$

Similarly, the backward LSTM computes the hidden states $h^{t(1)}$ and cell states $c^{t(1)}$ using the backward propagation equations:

$$h^{t(1)} = \text{LSTM\_backward}(x^t, h^{t+1(1)}, c^{t+1(1)})\ c^{t(1)} = \text{LSTM \_backward\_cell}(x^t, h^{t+1(1)}, c^{t+1(1)}) \quad (2)$$

Here, LSTM_forward and LSTM_backward are the LSTM computations in the forward and backward directions, respectively. LSTM_forward_cell and LSTM_backward_cell represent the cell computations in the forward and backward directions.The output of the BiLSTM at time step t is obtained by concatenating the forward and backward hidden states:

$$y^t = [h^{t(0)}, h^{t(1)}] \quad (3)$$

The concatenated output y^t represents the combined representation of the input sequence at time step t, capturing the information from both past and future contexts.

4.5.3 Hidden State and Cell State

The LSTM units in the BiLSTM layer maintained hidden states and cell states. The hidden states carried contextual information, representing the model's memory of past inputs, while the cell states controlled the flow of information through the network. These states were updated at each time step, allowing the BiLSTM to learn and remember important information throughout the sequence.

4.5.4 Dropout and Regularization

To prevent overfitting and improve generalization, dropout regularization was applied to the BiLSTM layer. Dropout randomly masked a proportion of the connections between the LSTM units, forcing the model to learn more robust and independent representations. This regularization technique helped mitigate the risk of overfitting and enhanced the model's ability to generalize to unseen data.

4.5.5 Time Distributed Layer:

Following the BiLSTM layer, a time-distributed layer was often employed to apply the prediction layer to each time step of the sequence. This layer allowed for independent predictions at each time step, facilitating the multi-label classification task of predicting the travel recommendations based on the extracted features.

4.5.6 Loss Function and Optimization:

The model was trained using a suitable loss function, mean_squared_error. Optimization techniques like stochastic gradient descent (SGD), Adam, or RMSprop were utilized in multiple experiments to minimize the loss function and update the model parameters iteratively during the training process. We finalized the Adam optimizer with a mean_squared_error loss function to minimize the errors. The mean squared error (MSE) loss function calculates the average squared difference between the predicted values and the actual values. When using the Adam optimizer, the update rule for the model's parameters is based on the gradients of the MSE loss. The formula for MSE with Adam optimizer can be represented as in equation 4:

$$MSE = (1 / n) * \Sigma(y\_pred - y\_actual)^2 \qquad (4)$$

Where n is the number of samples in the dataset, y_pred represents the predicted values and y_actual represents the actual values.

The Adam optimizer adjusts the model's parameters during training by calculating the gradients of the MSE loss and applying appropriate updates based on the adaptive learning rates for each parameter.

4.5.7 Hyperparameter Tuning:

The performance of the BiLSTM model was influenced by various hyperparameters, including the learning rate, batch size, number of LSTM units, dropout rate, and number of epochs. The hyperparameter tuning of this experiment is shown in Figure 3. These hyper parameters were tuned through experimentation to achieve the best balance between accuracy and generalization.

4.5.8 Training and Evaluation:

The model was trained on a portion of the dataset, and divided into training, validation, and testing sets. During training, the model iteratively adjusted its parameters to minimize the loss function on the training set. The performance of the model was evaluated using accuracy on the validation and testing sets to assess its effectiveness in recommending travel options based on the extracted features.

By utilizing the power of the BiLSTM architecture, the constructed recommender system effectively captured the sequential nature of the Malayalam travel reviews and learned intricate patterns and relationships within the data. The bidirectional processing, combined with regularization techniques, contributed to the model's ability to generate accurate recommendations based on the extracted features.

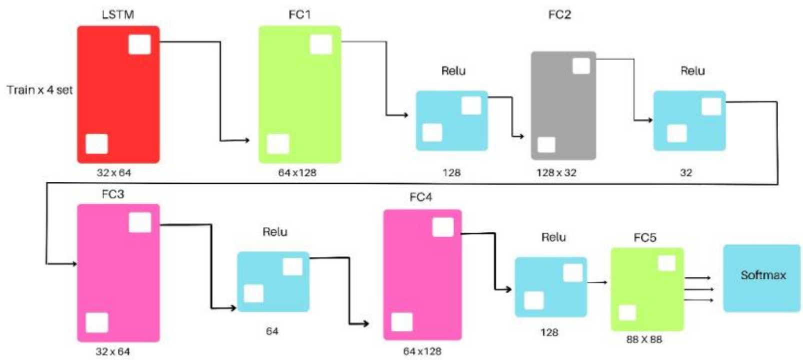

Figure 3 Model Architecture

V. EXPERIMENTAL RESULTS

The integration of a Bidirectional Long Short-Term Memory (BiLSTM) model provides a comprehensive and holistic perspective on the input sequence by leveraging information from both past and future contexts. This unique architectural design enhances the model's ability to accurately identify and interpret the distinctive features of textual travel patterns. By capturing contextual information from both directions, the BiLSTM model excels in tasks related to pattern matching, resulting in a deeper understanding and improved recognition and interpretation of travel patterns. During the experimentation phase, the architecture of the BiLSTM model underwent rigorous fine-tuning. Multiple combinations of optimizers, loss functions, and neural network architectures were explored to identify the most effective configuration. Only the refined and optimized version of the architecture is discussed and presented in this paper to ensure the highest performance.

The effectiveness of the model was evaluated using test and validation accuracies, which served as metrics to assess its performance in each phase of the research. To construct the BiLSTM architecture, several key parameters were carefully selected. The initial learning rate was set to 0.01, the loss function used was mean_squared_error, and the activation functions employed were Relu and softmax. The optimizer chosen was Adam, which has been widely recognized for its efficiency in optimizing deep learning models. The model was trained for a total of 1400 epochs, ensuring sufficient iterations for convergence and improved performance.

By employing this optimized BiLSTM architecture, the research aimed to achieve the highest level of accuracy and performance in predicting and interpreting travel patterns based on the extracted features from the Malayalam travel reviews. The chosen parameter settings and fine-tuning process aimed to maximize the model's potential and deliver reliable and robust results. Figure 4 shows the accuracy and loss of BiLSTM model perfomed according to the parameters discussed above.

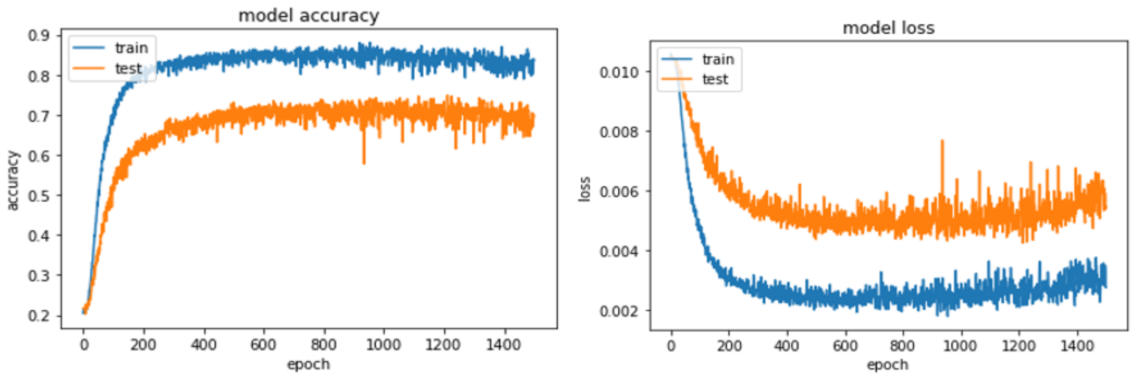

Figure 4 The learning curves of the experiment

VI. RESULT AND DISCUSSION

The objective of this study was to predict travel destinations by considering significant input variables such as travel type, mode of travel, location type, and location climate. These variables are key factors in determining user preferences for different destinations based on various combinations. To address this task, a BiLSTM model was constructed with multiple layers and activation functions, including ReLU and Softmax. During the training phase, the BiLSTM model demonstrated promising results, achieving a training accuracy of 83.65% and a training loss of 0.004. These metrics indicate that the model successfully learned the underlying patterns and relationships between the input variables and the corresponding travel destinations. The high training accuracy suggests that the model effectively captures the complexities of the data and performs well in predicting destinations based on the provided input.

In the subsequent validation phase, the model achieved a validation accuracy of 69.41% and a validation loss of 0.006. Although slightly lower than the training accuracy, this result demonstrates the model's ability to generalize and make accurate predictions on unseen data. The validation accuracy indicates that the model can effectively apply its learned patterns to new combinations of input variables, thereby providing reliable travel destination recommendations.

The performance of the BiLSTM model highlights its efficacy in capturing user preferences based on various input combinations. However, further analysis and experimentation are necessary to understand the factors contributing to the lower validation accuracy compared to the training accuracy. Future research can focus on enhancing the model's generalization capabilities and addressing potential limitations to improve the accuracy and reliability of travel destination predictions.

VII. CONCLUSION

In conclusion, this research aimed to develop a recommender system for travel destinations using Malayalam travel reviews. The study utilized a BiLSTM model to capture the underlying patterns and relationships between various input variables, including travel type, mode of travel, location type, and location climate. The results demonstrated the effectiveness of the BiLSTM model in predicting travel destinations based on the provided inputs. During the training phase, the model achieved a high accuracy of 83.65% and successfully learned the complexities of the data. The validation phase further confirmed the model's ability to generalize its learned patterns, achieving a validation accuracy of 69.41%. These findings highlight the potential of the BiLSTM model in personalized travel recommendation systems. By considering key input variables, the model can provide accurate and tailored travel destination suggestions to users. The integration of the BiLSTM architecture allows for the capture of contextual information from both past and future contexts, enhancing the model's capability to interpret travel patterns effectively.

While the results are promising, it is essential to address the observed difference between training and validation accuracies, indicating the scope for further improvements. Future research can focus on enhancing the model's generalization capabilities, exploring additional features, and incorporating user feedback to refine the travel recommendation system. Overall, this study contributes to the field of recommender systems by demonstrating the applicability of the BiLSTM model in the context of Malayalam travel reviews. The developed system holds the potential for providing personalized and accurate travel destination recommen- dations, facilitating enhanced user experiences and satisfaction. By leveraging the power of deep learning techniques, such as the BiLSTM architecture, we can unlock the full potential of travel recommendation systems and assist users in discovering their ideal travel destinations.

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